



**Intelligent Assistants for Flexibility Management  
(Grant Agreement No 957670)**

**D5.2 Initial iFLEX consumer engagement and incentive mechanisms**

**Date: 2021-07-10**

**Version 1.0**

**Published by the iFLEX Consortium**

**Dissemination Level: PU - Public**



**Co-funded by the European Union's Horizon 2020 Framework Programme for Research and  
Innovation under Grant Agreement No 957670**

## Document control page

**Document file:** D5.2  
**Document version:** 1.0  
**Document owner:** AUEB

**Work package:** WP5 Consumer engagement, incentive mechanisms and economic sustainability  
**Deliverable type:** R - Document, report

**Document status:**  Approved by the document owner for internal review  
 Approved for submission to the EC

## Document history:

Version	Author(s)	Date	Summary of changes made
0.1	Thanasis Papaioannou (AUEB)	2021-03-23	Initial table of contents
0.11	Christos Simoglou (OPTIMUS)	2021-06-14	Drafting of Section 6.1
0.15	Jussi Kiljander (VTT)	2021-06-15	Drafting of Section 6.3
0.2	Thanasis Papaioannou (AUEB)	2021-06-16	Drafted Section 4.1, 4.3, 4.5, 4.6
0.25	Trine Sørensen (INJET)	2021-06-17	Sections 4.2, 4.4
0.3	Roman Tomažič (ZPS)	2021-06-17	Section 4.10
0.35	Louise Birch Riley (INJET)	2021-06-17	Section 6.4
0.4	Dusan Gabrijelcic (IJS)	2021-06-17	Section 6.2
0.5	George D. Stamoulis (AUEB)	2021-06-18	Inserted Appendix
0.55	Thanasis Papaioannou (AUEB)	2021-06-18	Section 4.8, Section 4.9, Section 7
0.6	Thanasis Papaioannou (AUEB)	2021-06-24	Section 3, Section 5
	George D. Stamoulis (AUEB)	2021-06-28	Provided comments, mainly to entire document, and revisions/additions to Subsections 3.3, 3.4, 3.5 and 7.2
0.9	Thanasis Papaioannou (AUEB)	2021-07-02	Section 1, Section 2, Section 8, References, Final Editing
1.0	George D. Stamoulis (AUEB)	2021-07-07	Provided executive summary
1.0	Thanasis Papaioannou and George D. Stamoulis (AUEB)	2021-07-09	Final editorial check and applied reviewer comments

## Internal review history:

Reviewed by	Date	Summary of comments
Arso Savanovic (SCOM)	2021-07-05	Accepted with minor comments and modifications.
Isidoros Kokos (ICOM), Nikolaos Charitos (ICOM)	2021-07-06	Accepted with minor comments and modifications.

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## 1 Executive summary

The purpose of this deliverable is to report on the preliminary work carried out in Task 5.3 - Incentive mechanisms and consumer engagement, whose goal is to design and evaluate in the iFlex pilots economically efficient DR incentive mechanisms.

To this end, the deliverable first presents the basic definitions related to DR (Demand Response) and ADR (Automated Demand Response), the basic mathematical modeling for incentive mechanism design including the corresponding optimization problems encountered by the consumer and the operating entity running DR programs, and then overviews the main schemes proposed in the literature for price-based (i.e., implicit) and incentive-based (i.e., explicit) DR mechanisms, as well as associated issues such as targeting of the users to participate in a DR event, multiplicity and hierarchy of incentives etc.

In the sequel, the deliverable proceeds in the direction of non-economic incentives. In particular, the deliverable includes a broad overview of several already-published (in the literature) theoretical behavioral models (based on e.g. prospect theory, value-belief-norm theory etc.), mathematical formulations of user utility for energy consumption that incorporate behavioral aspects, and significant individual factors that affect energy-consumption behavior (such as motivation, opportunity, ability), as well as the implications of these to user incentives to participate in DR. Subsequently, the deliverable overviews engagement mechanisms, gamification approaches and eco-visualization approaches, all of which are considered as effective means to enhance user commitment to DR.

Furthermore, the deliverable overviews DR incentive mechanisms and the lessons learnt by prior and current DR deployments in the EU and overall, and particularly in the countries of the three pilot sites, namely Greece (interruptibility remuneration scheme and residential off-peak tariff), Slovenia (dynamic tariffing, which will be soon applicable) and Finland (dynamic energy and grid tariff prices, and incentive arising due to the organization of the balancing and reserve markets). Overall, in the EU and the world so far, predominantly DR schemes with economic incentives are provided and their rollout is still recent; however, DR schemes involving environmental and collective incentives have also begun to emerge.

Based on the practical constraints, the theories overviewed on designing and the practice on deploying DR incentive schemes, the deliverable proposes certain preliminary incentive schemes that are specifically customized for the three pilot sites of iFLEX project. For the iFLEX pilots in Greece and Slovenia, one of the schemes proposed is the use of rewards, by means of tokens or points that are redeemable; a specific model was developed (and will be assessed in further work of iFLEX WP5) on how the DR designer should select the rewards to maximize the expected flexibility to be obtained at the DR event within the available budget or to obtain the needed flexibility in expectation at the minimum budget. This scheme can be complemented by mechanisms such as environmental awareness, peer-pressure, user empowerment, by means of detailed analysis of electricity consumption and associated costs etc. For the iFLEX pilots in Finland, the primary objective is to exploit energy flexibility, while not affecting user comfort at all or if affected (even insignificantly) be properly compensated by means of incentives (not necessarily monetary). To this end, the deliverable proposes the use of either fixed rewards for participating residents that do not provide negative feedback throughout the duration of a DR event or variable rewards depending on when a resident provides such feedback, allowing for the possibility to only reward part of the residents; e.g., only the top percentage (e.g., 20%) of users in terms of their tolerance in DR. This scheme can be complemented by mechanisms such as peer-pressure and sharing of the value of flexibility.

The deliverable concludes by presenting requirements imposed to the iFLEX assistant and architecture by the above pilot incentive schemes, as well as an outline of future work.

## 2 Introduction and Objectives

The purpose of this deliverable is to report on the preliminary work carried out in Task 5.3 - *Incentive mechanisms and consumer engagement*. The intended audience is designers of DR mechanisms and flexibility services, energy service companies, DR aggregators, utility companies, DSOs, and any other interested stakeholders. No prerequisites are required for the understanding of this report. The goal of Task 5.3 is to design and evaluate in the pilots of iFlex economically efficient incentive mechanisms to stimulate consumers' engagement in Demand Response (DR) and Automated DR (ADR) programs. In this context, we will define novel consumer-customised rewards and contracts that will economically optimise the objectives of both the demand and the supply sides by utilising microeconomic social welfare optimisation methods. We will exploit aspects from behavioural economics by taking into account consumer behavioural traits (e.g. altruism) and extending incentives and policies accordingly. To this end, we will specify innovative socially aware incentives mechanisms that increase user awareness of the social welfare and their engagement to DR programs, and we will adapt the economic incentives mechanisms so that social priorities of consumers are also met. Special focus is given on designing mechanism that share the benefits of the DR fairly among all parties, including consumers.

The methodology followed in this deliverable is as follows: We first provide the basic definitions of DR and ADR, and then overview the main schemes proposed in the literature and/or practically employed for price-based and incentive-based DR mechanisms.

Then, we overview the basic mathematical modelling for incentive mechanism design and provide some related literature.

In the sequel, we revisit multiple existing theoretical behavioral models to extract mathematical insights, and also overview any existing mathematical formulation of user utility for energy consumption that incorporates behavioral aspects. We also overview significant individual factors that affect energy-consumption behavior based on the literature.

Then, we review user engagement mechanisms, gamification approaches and eco-visualization approaches.

We overview lessons learnt by prior and current DR deployments in EU and overall, and specifically in the countries of the three pilot sites, namely Greece, Slovenia and Finland.

Based on the practical constraints, the theory on designing and the practice on deploying DR schemes, we propose three preliminary incentive schemes specifically customized for the three pilot sites of this project.

This deliverable is structured as follows:

- Section 3 provides an overview of main explicit/implicit DR mechanisms and the mathematical framework for incentive-mechanism design (personalized or not).
- Section 4 reviews existing behavioral models and behavioral drivers of energy consumption.
- Section 5 overviews user engagement mechanisms, gamification mechanisms for energy conservation and eco-visualization approaches.
- Section 6 reviews DR schemes employed in the world and the pilot countries, and the lessons learnt thereof.
- In Section 7, we define our preliminary incentive mechanisms for the three pilot sites.
- Finally, in Section 8, we conclude this deliverable.

### 3 Explicit/Implicit DR incentives mechanisms

#### 3.1 What is DR? Overview of the main DR schemes in the Literature

Demand response (DR) consists of a set of signals to consumers of electricity that prompt the latter to adjust their electricity demand in response of these signals. Customer's response concerns change in the power consumption to better match the demand for power with the supply. Until recently electric energy could not be efficiently stored, so utilities have traditionally matched demand and supply by throttling the production rate of their power plants, turning on costly power generators, or buying expensive power in the real-time electricity market. There are certain limitations on what can be achieved on the supply side, because ramping up generation can take a long time, power may become very expensive to acquire, and demand can at times exceed by far the total supply of the grid. Demand response aims to address the problem by adjusting the power demand instead of the power supply.

Demand response programs encourage consumers (residential homeowners and business owners) to conserve energy during peak, high-demand times. Utility companies may send DR signals to their customers in a number of ways, e.g., announce smart metering during peak time periods and charge electricity at a higher tariff, while apply normal metering and tariffs in the off-peak time periods. The customer may adjust power demand by postponing some tasks that require large amounts of electric power or by cancelling some power-consuming activities, or she/he may decide to pay a higher price for their electricity. If renewable energy sources or batteries exist in the customer premises, some customers may shift part of their consumption to such alternate sources.

During times when the demand for electricity threatens to outpace the supply, utility companies will use these programs to help restore balance. DR can be considered as a technology-enabled economic rationing system for electric power supply. In demand response, voluntary rationing is accomplished by price incentives—offering lower net unit pricing in exchange for reduced power consumption in peak periods. Involuntary rationing, if employed, would be accomplished via rolling blackouts during peak load periods. Practically speaking, summer heat waves and winter deep freezes might be characterized by planned power outages for consumers and businesses if voluntary rationing via incentives fails to reduce load adequately to match total power supply. DR can help take the strain off the grid and ensure that everyone can enjoy the comforts of their HVAC system without fear of interruption. A few of the conditions that might necessitate this action include:

- Extreme temperatures
- Periods of scheduled maintenance
- Unexpected power line damages

DR programs may be broadly classified as price-based and incentive-based ones. In price-based programs, consumers adjust their electricity consumption schedules in response to price variations, so as to minimize their electricity bill. Dynamic prices may reflect the dynamic cost structure behind electricity generation, transport and ancillary services, thus dealing with the volatility of the power price in the wholesale market, the demand uncertainty and the inefficiencies in the mix of energy generators, such as the different costs for ramping up production per type of generator. Some representative price-based (also referred to as "**Implicit DR**") programs are:

- **Time-of-Use Pricing (TOU):** During pre-set daily peak periods, unit price increases by 100% as compared to the flat-rate tariff. This type of pricing adjustment applies to energy use over a set span of hours. For instance, "on-peak" might be from noon to 6:00 p.m. on a summer weekday, whereas "off-peak" refers to all other hours during the summer months. In this case, the price for each period will be pre-determined and invariable.
- **Critical-Peak Pricing (CPP):** On a set of selected days by the utility, peak-time prices are raised by a certain percentage (e.g., 500%), as compared to the nominal ones. Utility notifies the consumers one day in advance that peak prices will be in effect the following day. Critical peak pricing occurs when a utility observes or expects that wholesale market prices will spike, or when a power system experiences an emergency. If either of these situations occurs, the utility might designate certain time periods as "critical events". For instance, this might be from 2:00 p.m. to 4:00 p.m. on a summer weekday. In turn, electricity pricing during these peak periods raises significantly. There are two variations that exist for this type of rate design: (a) The time and duration of the price increase are



predetermined by anticipated events. (b) The time and duration of the price increase will vary, dependent on the grid's load reduction needs.

- **Real-Time Pricing (RTP):** With real-time pricing, electricity rates don't apply to broad periods. Rather, they apply to usage on an hour-by-hour basis. Prices are dynamically adjusted once in a certain time interval, of some minutes up to one hour, to reflect true production costs and/or wholesale market prices in this interval. To reduce uncertainty, prices per time interval are set one day in advance based on historical data and made public.
- **Variable Peak Pricing (VPP):** Variable peak pricing borrows from both TOU and RTP programs. Here, utilities will define in advance different electrical rates based on periods of time. For instance, the on-peak and off-peak hours described in TOU would still apply here. The difference? The price established for the on-peak period (e.g. noon to 6:00 p.m. on summer weekdays) will vary depending on the utility and local market conditions.

Some representative incentive-based schemes (also referred to as “**Explicit DR**”) are:

- **Direct Load Control (DLC):** Another type of demand response initiative, direct load control (DLC) programs allow power companies to cycle their air conditioning systems and water heaters on and off during periods of peak demand. When customers agree to this setup, utilities will reward them with financial incentives and reductions on their electric bills. This can be performed on the residential or commercial level. If your business is a light commercial power user, DLC programs can offer great savings with minimal inconvenience. In most cases, DLC-controlled equipment is controlled fewer than 10 times per year. Utilities may remotely shut down consumer appliances (such as air conditioners and water heaters) on a short notice. Alternatively, the operation mode of an appliance may be adjusted to one that is less energy-consuming. Customers receive upfront payments or discounts in their contracts as incentives, in order to adhere to the program and delegate the control of their appliances to the utility.
- **Load Curtailment Programs:** The participants are asked to reduce their consumption load to predefined values during system contingencies, in exchange for a discount or bill credit. Consumers that do not fulfil the requirements of the agreement may face penalties depending on the program terms and conditions.
- **Demand Side Bidding (DSB):** These programs are scheduled on a day-ahead timescale and incite customers to cast bids in offering to reduce their energy load. The price may be either part of their bid, or authority-posted based on the wholesale electricity market price. Participants whose load reductions offers are accepted, must either reduce their load as contracted or face a penalty.
- **Critical Peak Rebates (CPR):** Like CPP, critical peak rebates occur when utilities observe or expect that wholesale market prices will spike, or when a power system experiences an emergency. In either case, "critical events" are still called and the price for electricity during these periods remains the same as in PP. The only difference? Under CPR, utilities will refund customers at a single, pre-set value if they reduce their energy consumption beyond what they were expected to consume.

In incentive-based programs, consumers usually receive rewards, such as bill credits, discount on their bill or monetary compensation for their participation in the programs.

**Automated demand response (ADR)** is fully automated signaling from an electricity supplier that allows connectivity to the customer's control systems. Therefore, in ADR the DR signals are automatically generated and the electricity consumption at the customer premises is automatically adjusted.

The application of ADR varies from utility to utility. For example, Pacific Gas & Electric's ADR program<sup>1</sup> offers both incentives and technical assistance for customers willing to expand their energy management capabilities with ADR controls and management strategies. Customers that sign up receive automated event signals from PG&E to a technical solution that initiates the preprogrammed DR strategies. PG&E pays between \$200 and \$400 per kilowatt of DR load reduction, referred to as “dispatchable load,” that is controlled by the ADR technology. Participants receive 60 percent of that amount after verification of equipment installation and testing. The other 40 percent is paid after performance during a full demand response season, which may be up to 12 months. In addition, the ADR program incentives can be coupled with applicable and approved energy efficiency rebates, but they may not exceed 100 percent of total project cost.

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<sup>1</sup> <https://pge-adr.com/>

Austin Energy offers ADR to commercial customer<sup>2</sup> uses special thermostats for ADR. When directed by the utility, the thermostats automatically raising temperatures by several degrees for several hours during summer afternoons. In return, participants receive a preset price for each kilowatt saved. Additional power-saving measures include: (a) turning off non-essential lighting, signage and decorative features, (b) cycling refrigeration and HVAC systems, (c) delaying non-essential production. Experts suggest buildings may be able to reduce energy consumption 10 to 20 percent with ADR, particularly when teamed with fault detection and measurement and verification.

### 3.2 Overview of theory

In this section, we overview the basic mathematical modeling principles on successfully designing an effective DR scheme. We employ the real-time pricing (RTP) DR scheme proposed in (Li et al., 2011). In this scheme, given these prices, consumers take consumption-scheduling decisions aiming at welfare maximization. Moreover, household appliances include PHEVs (similarly to the Slovenian pilot) and batteries. For easiness in the presentation, we assume that batteries are not present and we omit the battery operation from the model of (Li et al., 2011), which is only presented below for completeness reasons. Each appliance provides a certain benefit to the user that is assumed for simplicity to depend on the pattern or volume of power it consumes. Each household owner aims to optimally choose its power-consumption schedule, so as to maximize its individual net benefit, i.e., the difference between consumption benefit and power cost, subject to various consumption and power-flow constraints. The objective of the distributed optimization process between the utility company and the consumers is to find optimal prices and power-consumption schedules that align individual optimality with social optimality, i.e., to find prices such that when households optimize their own net benefits, the social welfare is also optimized.

#### 3.2.1 The Model

A consumer  $n$  in  $\mathcal{N}$  is assumed to operate a number of appliances  $a$  in  $\mathcal{A}_n$ , such as HVAC, fridge, PHEV, etc. We consider a discrete-time model with a finite horizon that models a day. Each day is divided into  $T$  time slots of equal duration, indexed by  $t$  in  $\mathcal{T} = \{1, \dots, T\}$ . The utility company participates in wholesale electricity markets (i.e., day-ahead, spot market) to purchase electricity and then sells it to the  $\mathcal{N}$  customers. The utility company employs *dynamic pricing* in the retail market to coordinate the customers' power demand, so as to maximize the social welfare of the system. We assume that the utility company is regulated, so as to be social welfare maximizer rather than profit-seeker. The design of the retail dynamic prices should cover the operational costs of the utility company, including the cost for purchasing the power in the wholesale markets. We assume that this cost function  $C_t(L_t)$  at a time slot  $t$  is convex and increasing in the overall power demand  $L_t$ .

For each appliance  $a$  in  $\mathcal{A}_n$  of consumer  $n$ , we denote  $x_{n,a}^t$  its power draw at time slot  $t$  and by  $x_{n,a}$  the vector  $(x_{n,a}^t, t \in \mathcal{T})$  of its power draws over the entire day. For each appliance  $a$  in  $\mathcal{A}$ , there is a maximum and minimum power draw per time slot denoted by  $\gamma_{n,a}^{\min}$ ,  $\gamma_{n,a}^{\max}$  respectively, i.e.:

$$\gamma_{n,a}^{\min} \leq x_{n,a}^t \leq \gamma_{n,a}^{\max}, \quad \forall n \in \mathcal{N}, a \in \mathcal{A}_n, t \in \mathcal{T} \quad (1)$$

Depending on the appliance types, there is also a set of linear inequalities

$$A_{n,a} x_{n,a} \leq \eta_{n,a}, \quad \forall n \in \mathcal{N}, a \in \mathcal{A}_n, \quad (2)$$

where  $A_{n,a}$ ,  $\eta_{n,a}$  are appropriate matrices that model different appliance types, as it will be described in Section 3.2.3. Also, an appliance is characterized by a utility function  $U_{n,a}(\cdot)$  that quantifies the utility that consumer  $n$  obtains when appliance  $a$  consumes  $x_{n,a}^t$  power at time slot  $t$  in  $\mathcal{T}$ .

<sup>2</sup> <https://savings.austinenergy.com/rebates/commercial/offerings/load-management/load-co-op>

Each consumer  $n$  in  $\mathcal{N}$  is assumed to possess a battery that gives her greater flexibility on choosing her energy consumption schedule. We denote by  $B_n$  the battery capacity, by  $b_n(t)$  the energy level of the battery at time  $t$  and by  $r_n(t)$  the power (energy per period) charged to/discharged from the battery at time  $t$ . The battery is assumed to have no power leakage. Then, the battery energy-level is given by:

$$\begin{aligned} b_n(t) &= \sum_{\tau=1}^t r_n(\tau) + b_n(0) \\ 0 &\leq b_n(t) \leq B_n \\ r_n^{min} &\leq r_n(t) \leq r_n^{max} \\ b(T) &\geq \gamma_n B_n, \quad \gamma_n \in (0, 1], \end{aligned} \quad (3)$$

where  $r_n^{min}$ ,  $r_n^{max}$  are the lower and the upper bounds of the charge rate of the battery of consumer  $n$ , while  $b(T)$  is a minimum energy-level that should remain at the battery at the end of the day expressed as a fraction  $\gamma_n$  of the battery capacity  $B_n$ . Also, it is reasonably assumed that the battery cannot discharge more power than the appliances need, i.e.

$$-r_n(t) \leq \sum_{a \in \mathcal{A}_n} x_{n,a}^t. \quad (4)$$

The charging/discharging frequency of the battery is assumed to affect the battery lifetime. Thus, the cost of operating the battery is modelled by a convex function  $D_n(r_n)$  of the vector  $r_n = (r_n(t), t \in \mathcal{T})$ . This cost may correspond to the battery maintenance and amortized purchase cost over its lifetime.

Considering the battery, the total power demand for a consumer  $n$  in  $\mathcal{N}$  at each time slot  $t$  is given by:

$$Q_n(t) = \sum_{a \in \mathcal{A}_n} x_{n,a}^t + r_n(t). \quad (5)$$

### 3.2.2 Utility Company Problem

As already mentioned, the utility company is assumed to be regulated so as to aim maximizing social welfare, i.e.

$$\begin{aligned} \text{Maximize}_{\mathbf{x}, \mathbf{r}} : \quad & \sum_{n \in \mathcal{N}} \left( \sum_{a \in \mathcal{A}_n} U_{n,a}(x_{n,a}) - D_n(\mathbf{r}_n) \right) \\ & - \sum_{t \in \mathcal{T}} C \left( \sum_{n \in \mathcal{N}} Q_n(t) \right) \end{aligned} \quad (6)$$

such that all the equations (1)-(5) in Section 3.2.1 hold.

where  $\mathbf{x} = (x_n, \text{ for all } n \text{ in } \mathcal{N})$ ,  $x_n = (x_{n,a}^t, \text{ for all } a \text{ in } \mathcal{A}_n, t \text{ in } \mathcal{T})$ ,  $\mathbf{r} = (r_n, \text{ for all } n \text{ in } \mathcal{N})$  and  $\mathbf{r}_n = (r_n(t), \text{ for all } t \text{ in } \mathcal{T})$ .

The objective function of the utility company is concave and the feasible set is convex, and thus, in principle, an optimal solution could be calculated centrally. However, this would require knowledge of the utility (i.e. benefit) and cost functions of all customers, as well as all constraints, which is clearly unrealistic. The

strategy of the utility company is to properly select the price vector  $\mathbf{p} = (p(t), t \text{ in } \mathcal{T})$ , so as to make each customer choose the right consumption and charging schedules  $(x, r)$  that maximize social welfare.

### 3.2.3 User Problem

Given the price vector  $\mathbf{p}$  set by the utility company, each consumer  $n$  in  $\mathcal{N}$  chooses its consumption and battery-charging schedule  $(\mathbf{x}_n, \mathbf{r}_n)$ , so as to maximize its net benefit, i.e., the total utility from operating each appliance  $a$  in  $\mathcal{A}_n$  at power level  $x_{n,a}$  minus the cost of the electricity and the battery operation. Thus, each consumer  $n$  in  $\mathcal{N}$  solves:

$$\underset{\mathbf{x}_n, \mathbf{r}_n}{\text{Maximize}} : \sum_{a \in \mathcal{A}_n} U_{n,a}(x_{n,a}) - D_n(\mathbf{r}_n) - \sum_{t \in \mathcal{T}} p(t) Q_n(t) \quad (7)$$

The optimal choice  $(x_n(p), r_n(p))$  of the consumer  $n$  depends on the prices  $\mathbf{p} = (p(t), \text{ for all } t \text{ in } \mathcal{T})$  set by the utility company.

The user utility model depends on the user requirements regarding household activities driven by need, desire or habit. Moreover, the context of the user significantly affects the elasticity of a certain need, along with all demographic and socio-psychological factors, and other behavioural drivers described in Section 4.

Different appliances in the household are of different types based on how they consume electricity and on how consumers value the electricity consumption by the appliance. Depending on whether electricity consumption by an appliance can be deferred or not to a later time, appliances can be characterized as deferrable or non-deferrable respectively. Another important classification for appliances is whether their usage can be interrupted in time or not, referred to as interruptible or non-interruptible respectively. Moreover, depending on whether the amount of power consumed by an appliance can be reduced or not within the day, appliances can be categorized as elastic or inelastic respectively. There are appliance examples belonging to any combination of the aforementioned types. For example, HVAC appliances create non-deferrable, elastic and interruptible loads, while hair dryer and water heater have inelastic, deferrable and non-interruptible loads.

### 3.2.4 Equilibrium

The prices  $\mathbf{p}$  set by the utility company and the corresponding consumption and battery schedules of the consumers  $(x(p), r(p)) = (x_n(p), r_n(p))$ , for all  $n$  in  $\mathcal{N}$  are in equilibrium when  $(x_n(p), r_n(p))$  optimally solve the net benefit maximization problem for each consumer  $n$  in Section 3.2.3 and at the same time  $(x_n(p), r_n(p))$  is the optimal solution to the problem of the utility company in Section 3.2.2. There exists an equilibrium  $\mathbf{p}$  and  $(x, r)$  to the overall problem and

$$p^*(t) = C'(\sum_{n \in \mathcal{N}} Q_n^*(t)) \geq 0 \quad (8)$$

for each time  $t$ , as proved in (Li et al., 2011).

### 3.2.5 Other Work

There is a large number of works especially on mechanism design in smart grids. The demand response scenario of a cost-minimizing operator that incentivizes home users to shift their demands through dynamic pricing has been considered by (Gatzikis et al., 2011). In other works (Samadi et al., 2010), (Chen et al., 2012), where a social-welfare maximizing operator negotiates directly with utility-maximizing end-users, the optimal strategy is to set prices equal to the marginal cost of supply. (Samadi et al., 2011) derive convergent distributed algorithms based on auction mechanisms and dual decomposition methods, respectively. In addition, other works (Gatsis & Giannakis, 2011), (Fadlulah et al., 2013) cast the problem of demand response as a Walrasian auction, where prices are set so as to match supply and demand, and use tatonnement mechanisms for its solution. A centralized approach was followed by (Fadlulah et al., 2013b) where the power company iteratively informs a random user of the average energy price and the total hourly power consumption load. The user optimizes its own schedule so as to maximize her net benefit based on an energy-based value function and a cost function, and informs the utility company of the updated schedule. Finally, the case of price-setting for splitting the power demand across multiple utility companies is

considered by (Maharjan et al., 2013). Users optimally select their power demands from the utility companies based on the announced power prices, in order to maximize their utility functions within their budget in a Stackelberg-game setting, i.e., a game that is played sequentially by two players, where the first player has to optimally choose its strategy given that the second player chooses its strategy as best response to the strategy of the first player.

### 3.3 Incentives-based DR - Combination with DR targeting

Designing a successful DR program is challenging, as it depends on a multitude of factors (e.g., accuracy of user profiles for constructing representative user utility functions), but most importantly on the load curtailment actually attained by the consumers, involving their active participation or subject to an automated process. This implies that DR programs should be designed in a way that consumers are appropriately *triggered*—by means of either price signals, incentives or a combination of these—to actively participate in the program by modifying their consumption pattern so that the power demand during the peak hours is reduced. While all consumers can be eligible for DR, incentives are more effective when *customized* either with respect to the amount of curtailment required and/or to the offered amount of incentives. However, this gives rise to the *targeting process*; that is, which of the consumers will be selected in each DR event? Associated with this question is the objective of the entity running the DR event, e.g., offer the least total incentives to meet a particular DR goal (e.g., specific fraction of energy curtailment), or attain the maximum flexibility for a given budget of total DR incentives.

The main objective of (Chandan et al., 2014) was to propose a complete, practically applicable and scientifically justified approach to design efficient *customized incentive-based* DR and ADR programs by considering consumers' individual characteristics and context, in order to compensate for their discomfort induced to users by the modifications in their consumption patterns. In particular, it is argued in this article that whenever participating in DR a user should be offered incentives at least as high as her reduction in net benefit, that is loss of utility (due to discomfort) minus savings in the energy bill. Consumers' active participation could be attained by means of proper contracts and consumption schedules (acquired by means of either smart meters or load disaggregation), and therefore ensure the ADR programs' success. The authors proposed a methodology to utilize appliance level measurements in a utility function that represents the consumption behaviour of a single consumer and his/her associated comfort zone. The utility function introduced was exploited to define efficient incentives and targeting policies for ADR contracts in (Minou et al., 2015), which energy players such as providers and retailers can use in order to engage customers to ADR programs in an economically mutually beneficial manner. Two general cases regarding the available information may arise: (i) full information availability and (ii) partial information availability. Specific heuristic targeting policies were defined for both cases of information availability, achieving an effectiveness close to the optimal targeting (which is very complicated to solve accurately). Customer targeting can be considered in terms of personalized power-consumption reduction  $\Delta P$ , or in terms of personalized utility reduction  $\Delta U$ .  $\Delta P$  targeting may be convenient for maintaining utility reduction equal or bounded among selected customers, while  $\Delta U$  targeting may be convenient for achieving a specific power-consumption reduction from the selected customers.

Moreover, focusing on users' characteristics and how they can be leveraged to become of greater value for the society (through the success of the DR programs), specific behavioral characteristics delineating users' behavior (e.g. altruism) are incorporated in users' utility functions to study the impact on providers' goals and the proposed theoretical models in (Minou et al., 2017). A detailed overview of the behavioral drivers for energy consumption and the various behavioral models in the literature is provided in Section 4. In (Minou et al., 2017), different blends of population are considered, i.e., either only rational users or a mix of rational and altruistic users, with the latter being modelled by utilizing principles from behavioural economics. Building on users' utility models, an innovative net benefit-based maximization approach of incentives calculation is proposed accompanied with two policies that restrict in a different way the discomfort due to the demand reduction of users in DR, as well as a selection algorithm to target users for DR in the context of offering ADR contracts and on the basis thereof. The net benefit-based maximization approach of incentives calculation and the selection algorithm can be applied both in the full and partial information cases in (Minou et al., 2017).

Also, again for users exhibiting a degree of altruism (Papaioannou et al., 2018) employ a customer targeting approach, so that the DR designer constructs ADR contracts appropriately for customers to (a) enroll in them in the first place and (b) extend/renew their ADR contracts. The utility company offers ADR contracts to the residents of the district. Denote  $N$  the set of residential houses that enrol into the ADR programs. According to the ADR contract, the utility company curtails the total energy consumption of the house of a customer in



specific periods by a specific amount. A customer  $i$  enjoys net benefit  $U_i$  (i.e., user satisfaction minus energy cost) from consuming baseline energy  $q_0^i$  and an energy-consumption reduction  $\Delta Q_i$  in specific time periods according to an ADR contract results to a net benefit loss  $\Delta U_i = -\eta_i U_i$ . Note that  $\Delta Q_i$  may be calculated as a fraction of  $q_0^i$  or as a necessary energy curtailment, so as to bring energy load under a certain threshold. In return the customer receives an endowment  $b$  that can be personalized or not, and report on her/his satisfaction from the ADR contract provided. Overall, the DR designer aims to minimize the total endowment for achieving the needed energy curtailment, while maintaining the customer satisfaction ratio over a certain threshold. Customer targeting algorithms are proposed for both full and hidden information on user utility functions, based on customer feedback.

This approach is extended in (Papaioannou et al., 2018b) where an algorithm for optimal targeting of users is proposed in case of full information on their user utility functions. Also, based on customer feedback on different pairs of power curtailment and endowment, the targeting algorithm was experimentally shown to achieve performance close to optimal.

### 3.4 Multiple and hierarchical incentives

With decoupling and opening of energy systems, consumers can be under the influence of several, possibly conflicting, monetary incentives and/or price signals at the same time. Next three examples of such situations are provided to elaborate the issue:

1. **Explicit DR with prosumers:** In this case, the consumer has significant amount of own production provided, e.g. with solar panels. In many countries it is beneficial to consume your own energy because the price is much lower compared to the network price. For instance, in Finland the price for consumers' own energy is at maximum 1/3 of the network price, because consumers do not have to pay for taxes or the network fee (typically the price is even lower because the supplier does not pay the full market prices for your production). In this situation, participating to explicit DR programmes entails a conflicting incentive as it may make it impossible to fully consume one's own production.
2. **Explicit DR with dynamic electricity price:** In this case, the consumer is participating to implicit and explicit DR at the same time. With the emergence of aggregators, this situation will happen if a consumer is engaged with an aggregator and at the same time has an hourly changing electricity price (e.g., Nord Pool). In this situation, the aggregator (e.g., participating to TSO's reserve markets) may request flexibility from a consumer during low price periods, thus forcing the consumer to utilize electricity during the high price periods.
3. **Explicit DR with multi-vector energy system:** In this scenario, the consumer can utilize multiple energy sources (with different prices) for the same function (e.g., heating). This is the situation for example in the Finnish pilot, where the building's space heating and domestic hot water can be produced either with district heating (DH) or a heat pump. In this situation, it is beneficial for the consumer to utilize the cheapest option at any given time. However, if the heat pump is utilized for explicit DR it may be required to compensate with DH, thus increasing the costs of the consumer.

In all of the above examples, the consumer tries to optimize her energy consumption under different kinds of implicit DR scenarios (i.e., local production, dynamic electricity prices, multi-vector energy system). The explicit DR can be seen as an additional incentive that needs to be taken into account in the local optimization before making a decision whether to participate. To accomplish this, the DR designer should be able to estimate the costs caused from deviation from the optimal load profile. It should be noted that the above examples can be also combined. In this case, depending on the explicit DR program, there may actually be even four different incentives that need to be taken into account in the flexibility management.

So far, we have only dealt with multiple incentives faced by the consumer individually. We now turn attention to a **hierarchical scenario**, involving individual optimization of multiple actors at different levels. An ideal way to incentivise the DR is to optimise the usage of the end-user flexibility so that it satisfies multiple goals simultaneously. However, in practice, solving collectively this multi-facet optimisation problem will be hard, if not impossible. Therefore, when relevant, we can perform this optimisation at three stages and levels either bottom-up (i.e., from the end-user level to the market level) or top-down (i.e., from the market level to the end-user level). On one hand, bottom-up hierarchical optimization builds up on the availability of flexibility given optimal decision making at the lower level in an agnostic/myopic way of what is happening in the higher levels. For example, bottom-up optimization could happen as follows:

- 1) **Optimisation at the end-user level:** As described in the architecture of the iFlex framework, in D2.3, the iFlex assistant includes the automated flexibility management (AFM) unit. This unit

optimises the energy schedule for the end-users to minimise their energy cost while providing extra flexibility for the flexibility aggregator. In other words, this unit releases the incentivising potential of dynamic energy and grid tariff, explained in section 6.3.1, for DR.

- 2) **Optimisation at the aggregator level/energy community level:** The aggregator collects the flexibility potentials of several end-users, preferably using iFlex assistant. Internally, the aggregator should exploit flexibility availability and do self-balancing of electricity generation and supply, by also making use of storage resources to decide on the most cost-efficient schedule for buying electricity from the market. However, such kind of optimisation at the aggregator level is not in the scope of this project, since, iFLEX develops (in Task 4.3) an interface for the iFlex assistant to the aggregator platform.
- 3) **Optimisation in the market level:** Based on the flexibility availability at the aggregator level, the aggregator may decide when to submit a flexibility bid offer to the wholesale electricity markets or the auxiliary services markets. For this purpose, the aggregator needs to form a flexibility product according to the technical specification of end-user flexibility potential and submit an appropriate bid in the market. If the technical specification of flexibility offered by end-users allows forming more than one product, the aggregator could optimise his portfolio of bids across different products. It should be noted though that the aggregator should offer adequate incentives to the users, for otherwise they may not participate in the flexibility provision.

On the other hand, in top-down optimization, market is forecast to have the need for flexibility offers in certain time periods, in which if offered, they have a high market value. This market value is communicated to the aggregator level and then to the end-users in the form of incentives to provide flexibility in the specific time periods of need. The incentives provided should compensate the users for any discomfort arising from the flexibility offerings and any cost overheads in the electricity bill. Moreover, the incentives provided should not only make participating in the flexibility offerings profitable for the end-users, but also, they should render suboptimal any deviating action in terms of electricity consumption. In other words, the flexibility service provider sets the optimization framework for the aggregator and the end-users to optimally take their net benefit maximizing decisions. This top-down approach is followed in the construction of the preliminary incentive mechanisms in Section 7.

### 3.5 DR acceptance

Customer's adequate response to the DR signals, i.e., properly adjusting power consumption activities so as to shift or reduce power consumption within the time period of a DR event, cannot be taken for granted. This is often termed in the literature as "DR participation rate" (Wijaya et al., 2013) and it is a key metric for measuring the DR effectiveness. Since the users are assumed to be mostly rational and utility maximizers, the DR signal should render the appropriate response of the customer the best-response action.

However, consumers are not always perfectly rational. Thus, even if the incentives offered to them are considered a priori adequate to compensate them for their discomfort, it may happen that certain users do not participate in DR, either due to bounded rationality, or because of behavioral issues, which are overviewed in Chapter 4.

A model taking to account uncertainty in DR acceptance is introduced in (Chandan et al., 2014), which has already been overviewed in Subsection 3.3. In one of the models introduced in this article, DR targeting aims to select consumers to participate in an event at a particular time  $t$ , together with the consumption reduction per such consumer (subject to an upper bound on the permissible percentage of reduction), so that social welfare is maximized (i.e., total impact of discomfort is minimized) while the objective of the DR event on the total consumption is met. (This model does not include DR incentives, but could be combined with the incentives-based model of the same article, also overviewed in Subsection 3.3.) In the sequel, the authors extend the model by including a feature of uncertainty in DR acceptance. That is, it is taken that a targeted consumer does not necessarily conform to the DR signal, but rather this happens with a probability parameter. Therefore, the objective of DR targeting is now to maximize the expected social welfare while the objective of the DR event on the total consumption is met but now with respect to its expected value. The authors further explain that the value of this probability parameter is personal to each consumer, and can be estimated on the basis on information of each consumer's past behavior. In fact, they propose a model, where for a series of DR events (e.g. those during a month) a maximum number of participations per consumer is specified, in order to ensure fairness and avoid DR fatigue; in this case, DR acceptance probability can be taken that it equals the ratio of remaining participation times over the maximum number of participations. While this seems a reasonable assumption, it is preferable that AI-based user modelling is

employed, both for approximating the user-utility function as well as for estimating the DR acceptance probability. Of course, the model of user-utility function is a complicated task, because energy consumption is driven by a number of parameters that are hard to know. The aforementioned issue of DR fatigue can be taken into account by utilities in their modelling of DR uncertainty. In general, it can be reasonably expected that the higher the uncertainty of DR acceptance, the higher the number of consumers that should be targeted, and the higher the variation in the actual total consumption after DR.



## 4 Behavioral traits affecting incentives

### 4.1 Overview of theory on behavioral aspects

Andrew Darnton's Practical Guide to Behaviour Change models (Darnton, 2008a) provides a framework for developing interventions based on behavioural models. It is supported by the Reference Report (Darnton, 2008b) which gives a thorough review of the different social-psychological models and theories of behaviour. The models and theories cover a range of different focal points or variables of behaviour, among others:

- Values, Beliefs and Attitudes
  - Theory of Reasoned Action
  - Value Beliefs Norm Theory
- Norms and Identity
  - Norm Activation Theory
  - Social Identity Theory
- Agency, Efficacy and Control
  - Theory of Planned Behaviour
  - Theory of Self Efficacy
- Habit and Routine
  - Theory of Interpersonal Behaviour
- Economic Assumption
  - Expected Utility Theory.

Table 1 below provides a brief overview of these theories/models.

Table 1: Overview of a selection of behavioural models and theories.

Themes	Theory	Overview
Values, Beliefs and Attitudes	Theory of Reasoned Action	The attitudinal component is the dominant factor. Claims that the individual's beliefs about behavioural outcomes and his/her evaluation of those outcomes determine his/her attitudes to the behaviour. Intentions directly lead to behaviour.
	Value-Belief-Norm Theory	Explains the influence of human values on behaviour in an environmentalist context. The value components include altruistic values, biospheric values, egoistic values, and openness to change values. Holds that green behaviours are more likely to occur when a causal series of variables (i.e., values, beliefs and personal norms) is present.
Norms and Identity	Norm Activation Theory	Describes the process by which personal norms are activated. Involves two stages: 1) the individual feels an awareness of the consequences of their own action for others, and 2) the personal costs of acting are calculated with the result that responsibility may be denied.
	Social Identity Theory	Social identity theory addresses the ways that social identities affect people's attitudes and behaviours regarding their ingroup and the outgroup. Explains the processes by which groups of individuals tend to differentiate themselves from one another: <ol style="list-style-type: none"> <li>1. Categorization, by which Individuals identify themselves with like others in an in-group and differentiate themselves from the out-group</li> <li>2. Self enhancement, through which individuals favour the in-group, and promote themselves relative to others.</li> </ol>

Agency, Efficacy and Control	Theory of Planned Behaviour	Resulting from a revision of the Theory of Reasoned Action by including the construct of Perceived Behavioural Control (PBC). PBC is a construct which is heavily based on self-efficacy. Holds beliefs as the “underlying foundations” of behaviour (habits is not incorporated as a factor influencing behaviour).
	Theory of Self Efficacy	Self-efficacy is the conviction that one can successfully execute the behaviour required to produce the outcomes. Self-efficacy mediates the influence of motivations on behaviour - if the behaviour is deemed impossible it will not be undertaken (despite motivation being present).
Habit and Routine	Theory of Interpersonal Behaviour	Behaviour is a function partly of the intention, partly of the habitual responses, and partly of the situational constraints and conditions. Behaviour is influenced by moral beliefs, but the impact of these is moderated both by emotional drives and cognitive limitations.
Economic Assumption	Expected Utility Theory	Individuals make behavioural decisions based on a calculation of the expected costs and benefits. Irrational behaviour can have a rational explanation. Rational choice is an assumption not a guiding principle in economic analysis.

In the context of environmental behaviours, which are of highest interest for energy-related decisions, the Theories of Planned Behaviour, Value-Belief-Norm theory and the Norm Activation theory have often been applied (Sawitria et al., 2015). The following will provide a more detailed overview of each of these theories.

## 4.2 The Theory of Planned Behaviour

The theory of planned behaviour (TPB) is one of the main cited and applied behaviour theories. It has been used extensively in health domain and it is also widely used research on pro-environmental behaviour. In TPB, the attitude toward the behaviour, the subjective norms, and the perceived behavioural control all together inform an individual’s behavioural intention. The stronger the intention the more likely the behaviour will be performed and that a behavioural change will occur. In other words, intention is the antecedent of a behaviour<sup>3</sup>.

Intention is itself an outcome of the combination of attitudes towards a behaviour. That is the positive or negative evaluation of the behaviour and its expected outcomes, and subjective norms, which are the social pressures exerted on an individual resulting from their perceptions of what others think they should do and their inclination to comply with these. The TPB added a third set of factors as affecting intention (and behaviour); perceived behavioural control. This is the perceived ease or difficulty with which the individual will be able to perform or carry out the behaviour, and is very similar to notions of self-efficacy (Morris et al. 2012).

<sup>3</sup> In behavioural psychology, an antecedent is a stimulus that cues an organism to perform a learned behaviour.

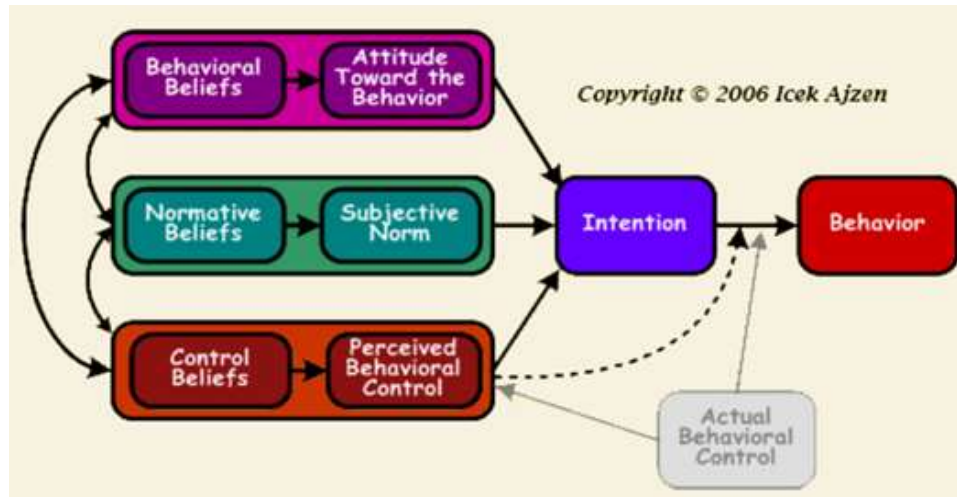


Figure 1: Theory of Planned Model by (Ajzen, 1991)

The elements in the TPB model (see Figure 1) has been described by the father of the theory (Ajzen, 1991), as follows:

**Behavioral Beliefs** link the behaviour of interest to expected outcomes. A behavioural belief is the subjective probability that the behaviour will produce a given outcome. The evaluation of each outcome contributes to the attitude in direct proportion to the person's subjective probability that the behaviour produces the outcome in question.

**Attitude toward a behavior** is the degree to which performance of the behaviour is positively or negatively valued. According to the expectancy – value model, attitude toward a behaviour is determined by the total set of accessible behavioural beliefs linking the behaviour to various outcomes and other attributes.

**Normative beliefs** refer to the perceived behavioural expectations of such important referent individuals or groups as the person's spouse, family, friends, teacher, doctor, supervisor, and co-workers (depending on the population and behaviour studied). It is assumed that these normative beliefs (in combination with the person's motivation to comply with the different referents) determine the prevailing subjective norm. Specifically, the motivation to comply with each referent contributes to the subjective norm in direct proportion to the person's subjective probability that the referent thinks the person should perform the behaviour in question.

**Subjective norm** is the perceived social pressure to engage or not to engage in a behaviour. Drawing an analogy to the expectancy-value model of attitude (see attitude toward the behaviour), it is assumed that a subjective norm is determined by the total set of accessible normative beliefs concerning the expectations of important referents.

**Control beliefs** have to do with the perceived presence of factors that may facilitate or impede performance of a behaviour. It is assumed that these control beliefs (in combination with the perceived power of each control factor) determine the prevailing perceived behavioural control.

**Perceived behavioural control** refers to people's perceptions of their ability to perform a given behaviour (self-efficacy). Drawing an analogy to the expectancy-value model of attitude (see attitude toward the behaviour), it is assumed that perceived behavioural control is determined by the total set of accessible control beliefs, i.e., beliefs about the presence of factors that may facilitate or impede performance of the behaviour. To the extent that it is an accurate reflection of actual behavioural control, perceived behavioural control can, together with intention, be used to predict behaviour.

**Intention** is an indication of a person's readiness to perform a given behaviour, and it is considered to be the immediate antecedent of behaviour. The intention is based on attitude toward the behaviour, subjective norm, and perceived behavioural control, with each predictor weighted for its importance in relation to the behaviour and population of interest.

**Behavior** is the manifest, observable response in a given situation with respect to a given target. Single behavioural observations can be aggregated across contexts and times to produce a more broadly representative measure of behaviour. In the TPB, behaviour is a function of compatible intentions and perceptions of behavioural control. Perceived behavioural control - as a proxy for actual control - is expected

to moderate the effect of intention on behaviour, such that a favourable intention produces the behaviour only when perceived behavioural control is strong.

Successful performance of a behaviour depends not only on a favourable intention but also on a sufficient level of behavioural control. **Actual behavioural control** refers to the extent to which a person has the skills, resources, and other prerequisites needed to perform the behaviour in question. In many situations, it may be difficult or impossible to ascertain a person's level of actual control. However, to the extent that perceived behavioural control is accurate, it can serve as a proxy for actual control and be used for the prediction of behaviour.

A literature review and analysis by (Sniehotta, 2009) show that one of the limitations of the TPB is the effect sizes found by using only these three factors to explain behaviour(al intention). Moreover, the correlation between knowledge or awareness and actual behaviour are not found for most studies (Sniehotta, 2009; Kolmuss & Agyeman, 2002). This point is also stated by (Darnton, 2008b). Additionally, Darnton stresses the other influential factors in behavioural change apart from values, beliefs, and attitudes which do come up in other theories. Furthermore, as a general critique, Darnton emphasizes the limits of behavioural models. According to Darnton (2008a), the behavioural change intervention should be grounded in theory and the analytical strengths of these models should be used to evaluate the intervention. However, they should be used as tools and not as templates where all factors not found in the particular model are disregarded.

### 4.3 Value-Belief-Norm Theory

(Stern et al., 2000)'s Value-Belief-Norm (VBN) theory considers five individual-level variables that impact environmentally significant behavior. In this theory, these variables are causally related such that values and beliefs activate personal norms for pro-environmental behavior. However, it is also posited that variables earlier in the sequence can directly affect variables later in the sequence (i.e., direct and indirect effects).

The beginning of the causal sequence is an *individual's personal values*. Values (e.g., altruism) orient an individual toward stewardship of others and his or her surroundings. These values, in turn, shape the individual's beliefs concerning the impact of human activity on the environment. For example, an individual possessing a value system in which the environment is for personal consumption is less likely to believe that human activity is damaging the environment. In VBN, an individual's belief about the environment is labeled *environmental (or ecological) worldviews*, and it represents the second variable in the causal sequence.

An individual's environmental worldview can have an impact on his or her recognition of the negative consequences resulting from environmental problems for objects that are valued by the individual (e.g., children, quality of life). For example, an individual who believes that human activity is harming the environment in general is likely to recognize how human activity is producing specific negative consequences for objects that are valued by the individual. In VBN, the *individual's awareness of the adverse consequences of environmental problems for valued objects* is the third variable in the causal sequence.

Once the individual becomes aware of the problem, the individual assesses his or her personal responsibility for the negative consequences for the valued object (i.e., ascription of responsibility; Schwartz, 1977). It includes assessment of the role of the individual's behavior in creating the problem (e.g., throwing away glass bottles) and his or her ability to behave in ways that could reduce the problem (e.g., recycling). Thus, the fourth variable is the *individual's belief that he or she can initiate action to reduce the adverse consequences*. It is important to note that the belief that actions are available to reduce the problem is different from an individual's self-efficacy beliefs, which is one's belief in his or her ability to take these actions. The four preceding variables lead to activation of an individual's personal norms concerning pro-environmental behavior. Therefore, the fifth variable is *the individual's personal norms concerning his or her responsibility to take pro-environmental action*. Lastly, the individual's environmental personal norms impact his or her behaviors. To sum up the five individual-level variables that influence energy-consumption behavior according to VBN theory are:

- Individual personal values
- Environmental worldviews
- Problem awareness
- Individual belief that own action can have an impact
- Personal norms

The VBN theory identifies **four different classes** of environmentally significant behaviors that are impacted by environmental personal norms. The first class consists of environmental activism behaviors, including participating in demonstrations, active involvement in environmental groups, and actively lobbying lawmakers for environmentally friendly laws. This first class of behaviors represents *public activism* in support of environmental protection.

The second class of behaviors consists of public non-activism behaviors, including policy support (e.g., support for tax credits on alternate-fuel vehicles) and environmental citizenship behaviors (e.g., donations to environmental causes). This class of behaviors also represents *acceptance and support of policies for environmental protection*.

The third class of behaviors consists of nonpublic environmental behaviors (e.g., consumer purchases, use and disposal of household products). This class represents an *individual's behaviors and choices in his or her daily routines and life*.

The fourth class is *behavior in organizations*. Stern argued that this last class of behaviors includes the way in which individuals perform their jobs (e.g., choice of materials, equipment) and behave in organizations in general (e.g., turning off lights and computers, recycling).

(Scherbaum et al., 2008) employed the VBN model at an office context and based on a survey on employees on large state university in USA, they established that environmental personal norms are a predictor of self-reported energy conservation behaviors and of behavioral intentions. Also, environmental personal norms were found to mediate the relationship between environmental worldviews and self-reported energy-conservation behaviors and behavioral intentions.

(Frederiks et al., 2015) review **the socio-demographic** and **psychological** predictors of residential energy consumption. According to Frederiks et al., the socio-demographic factors that mainly influence the energy consumption of residential users are:

- Household income and employment status. The more income, the more energy consumption.
- Household size. The bigger the household, the more energy consumption.
- Dwelling size and detachment. The dwelling size is positively correlated to the consumption. Detached houses tend to consume more energy than apartments of the same size.
- Stage of family life-cycle. The stage of a family's life cycle—typically defined as a combination of criteria such as family members' age, marital status, and family size/type—appears to be one of the strongest predictors of household energy consumption residential energy consumption.
- Geographical location of the house is an important factor that influences energy consumption for heating/cooling and humidification/dehumidification.
- Education and Technological Expertise. People with higher technological expertise tend to consume less energy, due to more efficient appliances or home automation or better knowledge on saving energy.

Also, according to (Frederiks et al., 2015), the psychological factors that mainly influence the energy consumption of residential users are:

- Knowledge and problem awareness, as was the case in (Stern, 2000)'s Value-Belief-Norm (VBN) theory. The absence of a direct link between knowledge and action is often referred to as "knowledge-action gap".
- Attitude to environmental problems, as was the case in VBN theory. Therefore, the link of attitude to pro-environmental behavior is characterized as loose, referred to as "value-action gap".
- Intrinsic motives, perceived personal responsibility and personal moral norms. This factor is similar to the values and personal norms in VBN theory. However, the strength of this relationship may be weak due to the same processes implicated in the aforementioned "value-action gap".
- Locus of control. Locus of control reflects a person's perception of whether they have the capability to enact change and/or control events that impact them (internal locus of control implies the belief that own action can have a significant impact). This factor is related to the individual belief that own action can have an impact in VBN theory.
- Perceived cost/benefit ratio. People are often motivated by self-interest and try to select alternatives that yield the highest benefit for the lowest cost—where "benefits" and "costs" may include *scarce* or valued resources such as time, effort, money, social status/acceptance, convenience, comfort, and so forth. For employees, this is related to the choices regarding daily behavior and the behavior in



organizations classes of the VBN theory. Several categories of perceived advantages and disadvantages may be taken into account:

1. Personal disadvantages (e.g., beliefs regarding loss of comfort, coldness, unhealthiness, behavioral constraints, etc. imposed by an energy-saving lifestyle),
  2. Societal advantages (e.g., social status acceptance, beliefs regarding less environmental pollution, more energy for future generations, world energy supplies, etc.),
  3. Personal responsibility (e.g., beliefs regarding a sense of duty/responsibility),
  4. People short-sighted for immediate costs or benefits, but more farsighted for future ones. In daily life, there are countless situations where people procrastinate, postpone decisions, or delay actions because they are viewed as costly in the short-term, despite offering long-term benefits.
- Personal comfort: Personal comfort, particularly the perceived loss of comfort that any energy-saving measure might impose, may have a sizeable impact on energy consumption. Any decrease in personal comfort, or perceived threat to lifestyle quality, may reduce the likelihood of engaging in conservation behavior and this is related to the daily behavior class of the VBN theory.
  - Normative social influence: It is well established that human beings make social comparisons, follow the behavior of other people, conform to social norms—i.e., the explicit and/or implicit rules, guidelines or behavioral expectations within a group or society that guide what is considered normal and/or desirable. It is expected that in an organizational environment, the normative social influence is even more important as a driver for energy-consumption behavior than in a residential environment.

#### 4.4 Norm Activation Theory

Schwartz's Norm Activation Theory (Schwartz 1977) distinguishes between social norms and personal norms (see Figure 2). While personal norms are considered as stemming from the individual's innate values, these innate values are at the same time described as being internalised from social norms. As an innate value, there is more focus on the emotions invested in acting according to one's personal norms, which is used to explain altruistic or 'helping' behaviours.

The theory was grounded on the premise that three determinants: i) awareness of consequences, ii) ascription of responsibility, and iii) personal norms, directly provide the motivational basis for an individual to behave pro-environmentally.

The model below illustrates the stages by which personal norms are activated; it suggests that as individuals become aware of the consequences of their own actions (stage 1), they will calculate their personal costs of reacting resulting in ascription (or denial) of their responsibility (stage 2). As a result, their personal norm(s) are activated which will then motivate or trigger the associated behaviour.

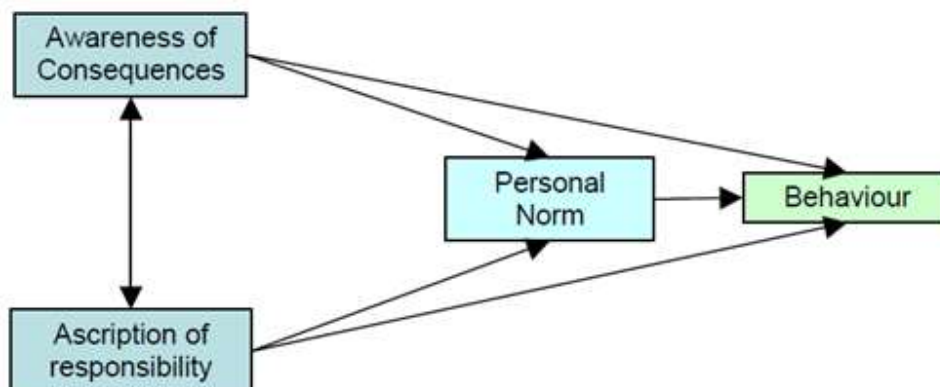


Figure 2: Swartz's norm activation theory (Shalom H. Schwartz, 1977) [reproduced from (Jackson, 2005)]

This model has been used to explain and predict pro-environmental behaviours (considered to be altruistic behaviours), although it can also be used to account for why, in some situations, people fail to help referred to as "denial of responsibility" (Darnton, 2008b). Higher awareness of consequence will cause higher

ascription of responsibility as well, and higher personal norms accordingly. Personal norms will, in the end drive someone to act pro-environmentally which causes a higher rate of pro-environmental behaviours.

Indeed, the value of personal norms for various types of pro-environmental behaviours in different contexts have been demonstrated in several studies e.g., (Vining & Ebreo, 1992), (Thøgersen, 1996), (Harland et al., 1999) where acting pro-environmentally is tied to the individual's moral and altruistic values (see also Fritzsche & Oz 2007). Personal norm is a moral obligation for the individual to act a certain way whether that, in the pro-environmental context, means doing a certain behaviour (e.g., turn off lights when leaving the room) or avoid doing a certain behaviour (taking very hot and long showers). Through the awareness of consequences and ascription of responsibility, the individual will thus reflect more closely on their own contribution to a (pro)environmental issue and their ability to solve the issues (Esfandiar et al. 2019).

#### 4.5 Prospect Theory

Economists typically assume that market behavior is motivated primarily by material incentives, and that economic decisions are governed mainly by self-interest and rationality. In this context, rationality means that decision-makers use available information in a logical and systematic way, so as to make optimal choices given the alternatives at hand and the objective to be reached. It also implies that decisions are made in a forward-looking way, by fully taking into account future consequences of current decisions. In other words, so-called extrinsic incentives are assumed to shape economic behavior.

In psychology, especially cognitive psychology, a human being is commonly regarded as a system, which codes and interprets available information in a conscious and rational way. But other, less conscious, factors are also assumed to govern human behavior in a systematic way. It is this more complex view – where intrinsic incentives help shape human behavior – that has come to penetrate recent developments in economic theory.

Economists have traditionally treated a decision-maker's preferences over available alternatives as fixed and given. The decision-maker is assumed to form probabilistic beliefs or expectations about the state of nature and the effects of her actions, and to process available information according to statistical principles. More precisely, standard economic theory relies on the expected-utility maximization approach founded by (von Neumann & Morgenstern, 1944) and extended by (Savage, 1953). Here, it is presumed that for every decision-maker there exists some real-valued function  $u$ , defined on the relevant set  $X$  of outcomes  $x_1, x_2, \dots, x_l$ , such that if one available action  $a$  results in probabilities  $p_i$  over the outcomes  $x_i$  (for  $i=1, \dots, l$ ) and another available action  $b$  results in probabilities  $q_i$  over the same outcomes, then the decision-maker (strictly) prefers action  $a$  to action  $b$  if and only if the statistically expected value of this "utility function"  $u$  is greater under  $a$  than under  $b$ .

Formally, the criterion for choosing  $a$  is thus

$$\sum_i p_i u(x_i) > \sum_i q_i u(x_i) \quad (9)$$

By contrast, cognitive psychologists consider an interactive process where several factors may influence a decision in a non-trivial way. These components include perception, which follows its own laws, as well as beliefs or mental models for interpreting situations as they arise. Intrinsic motives, such as emotions – the state of mind of the decision-maker – and attitudes – stable psychological tendencies to relate to a given phenomenon in one's environment – may influence a decision. Moreover, the memory of previous decisions and their consequences serves as a critical cognitive function that also has a strong influence on current decision-making. Given this complex view, human behavior is regarded as locally conditioned to a given situation. Typically, behavior is adaptive; it is dependent on the context and transitory perceptual conditions.

Departures from the von Neumann-Morgenstern-Savage expected-utility theories of decisions under uncertainty were first pointed out by the 1988 economics laureate Maurice Allais (1953) (Allais, 1953), who established the so-called Allais paradox. For example, many individuals prefer a certain gain of 3,000 dollars to a lottery giving 4,000 dollars with 80% probability and 0 otherwise. However, some of these same individuals also prefer winning 4,000 dollars with 20% probability to winning 3,000 dollars with 25% probability, even though the probabilities for the gains were scaled down by the same factor, 0.25, in both alternatives (from 80% to 20%, and from 100% to 25%). Such preferences violate the so-called substitution

axiom of expected-utility theory<sup>4</sup>. Kahneman has provided extensive evidence of departures from the predictions of expected utility (see (Kahneman & Tversky, 1979), (Tversky & Kahneman, 1991), (Tversky & Kahneman, 1992), (Kahneman & Lovallo, 1993), (Kahneman et al., 1990)).

In contrast to von Neumann-Morgenstern-Savage utility theory, prospect theory postulates the existence of two functions,  $v$  and  $\pi$ , such that the decision-maker (strictly) prefers action  $a$  over action  $b$  if and only if

$$\sum_i \pi(p_i)v(\Delta w_i) > \sum_i \pi(q_i)v(\Delta w_i), \quad (10)$$

where  $\Delta w_i = w_i - w_0$  is the deviation in wealth from some reference level  $w_0$  (which may be initial or aspired wealth, see below).

There are three differences between the two models. First, in prospect theory, the decision-maker is not concerned with final values of wealth per se, but with changes in wealth,  $\Delta w$ , relative to some reference point. This reference point is often the decision-maker's current level of wealth, so that gains and losses are defined relative to the status quo. But the reference level can also be some aspiration level: a wealth level the subject strives to acquire, given his or her current wealth and expectations. Kahneman and Tversky argued that a decision problem has two stages. It is "edited", so as to establish an appropriate reference point for the decision at hand. The outcome of such a choice is then "coded" as a gain when it exceeds this point and as a loss when the outcome falls short of it. This editing stage is followed by an evaluation stage, which is based on the criterion in inequality (10).

The second difference relative to expected-utility theory concerns the value function  $v$ . In addition to being defined over changes in wealth, this function is S-shaped. Thus, it is concave for gains and convex for losses, displaying diminishing sensitivity to change in both directions. Furthermore, it has a kink at zero, being steeper for small losses than for small gains. The function  $u$  in expected-utility theory, by contrast, is usually taken to be smooth and concave everywhere. The form of the value function is illustrated in Figure 3.

Third, the decision-weight function  $\pi$  is a transformation of the objective probabilities  $p$  and  $q$ . This function is monotonically increasing, with discontinuities at 0 and 1, such that it systematically gives overweight to small probabilities and underweight to large probabilities. Its typical shape is illustrated in Figure 4.

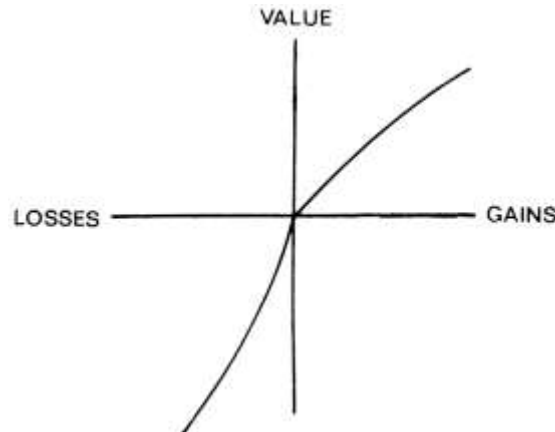


Figure 3: The value function according to prospect theory<sup>12</sup>.

<sup>4</sup> By this axiom, if a decision-maker prefers lottery A to B, he should also prefer a probability mixture  $pA + (1-p)C$  to the probability mixture  $pB + (1-p)C$ , for all lotteries C.



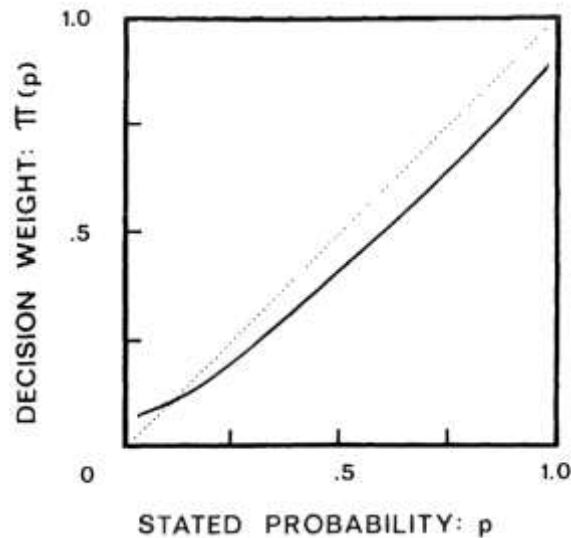


Figure 4: The decision-weight function  $\pi$  overweighs low probabilities and underweighs large probabilities.

These differences make prospect theory consistent with the experimental evidence mentioned earlier in this section. Since people evaluate risky prospects on the basis of changes in wealth relative to some reference level, appropriate assumptions about the editing stage would make the model consistent with the common observation that people choose differently depending on how a problem is framed. The kink on the value function at the reference point (i.e., making the function much steeper for small losses than for small gains) implies that choices are consistent with loss aversion. As a consequence of the diminishing marginal sensitivity to change in the  $v$  function, decision-makers become risk averse towards gains (they value large gains less than proportionally) and risk loving towards losses (they value large losses more than proportionally), in line with the evidence. Moreover, the fact that the decision-weight function overweighs small probabilities and underweighs large probabilities can explain the Allais paradox.

Prospect theory and its extensions have taken important steps towards a more accurate description of individual behavior under risk than expected-utility theory. It now forms the basis for much of the applied empirical work in this field.

#### 4.6 Motivation, Opportunity, Ability Behavioral Model

A model of the consumer behavior towards environmental protection is the motivation- opportunity-ability (MOA) (Ölander and Thøgersen, 1995). This model defines three main factors that influence behavior: motivation, opportunity and ability. Motivation is determined by the beliefs about and evaluation of outcomes of a behavior, which in turn influences the attitudes towards certain behavior and the intention to actually perform the behavior. In addition, the intention to perform certain behavior is influenced by social norms concerning the behavior. This social norm refers to the subjective norm of the theory of reasoned action, which is a person's perception of how others think one should or should not act (Ajzen and Fishbein1980). The factors ability and opportunity facilitate the step from intention to the actual performance of behavior. Ability to perform the behavior is based on knowledge about how to perform the behavior as well by habits which 'shortcut' the intentional process. Opportunities are contextual circumstances (external factors) that make performance of behavior convenient or can trigger certain behavior, for instance the placement of waste containers close to someone's home.

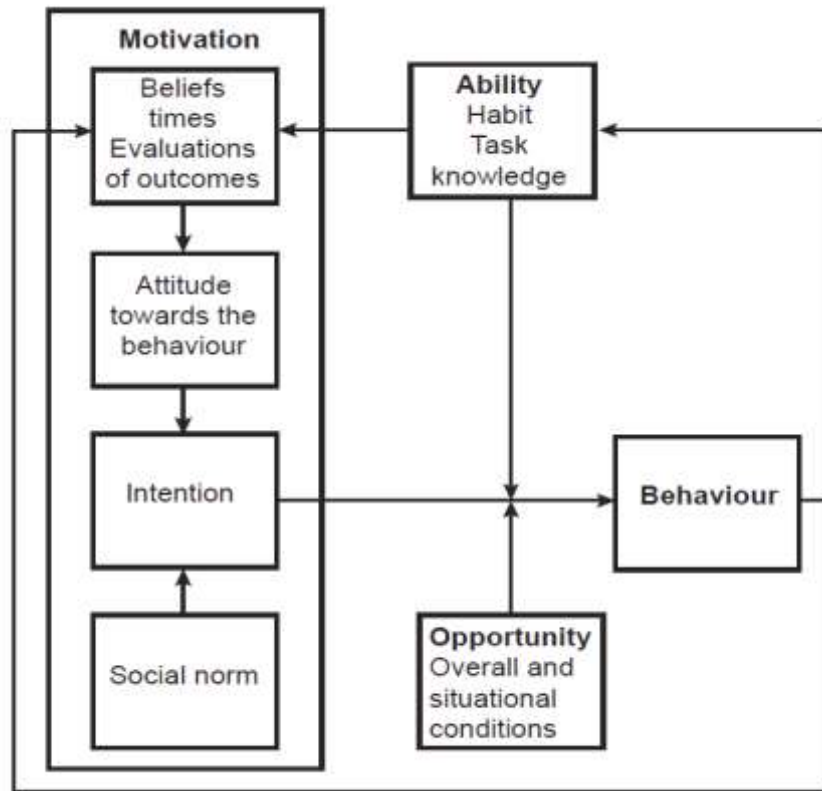


Figure 5: MOA behavioral model.

#### 4.7 Fogg's Behavioral Model

A model that is closely related to the MOA model, is the Fogg behavior model (Fogg, 2009), which is intended to support the design practice in stimulating certain behavior. This model states that the higher motivation and ability are, the more likely it is that a person performs the target behavior (Figure 6). Triggers can be used to increase ability and/or motivation. Examples of triggers are the alarm of a kitchen timer or a message that you should return books to the library. According to Fogg, triggers are to be used first to stimulate certain behavior. If that is not sufficient, one has to focus on improving ability. Triggers and ability are easier to address than motivation. A trigger in the Fogg behavior model is comparable to 'opportunity' in the MOA model. Both refer to changes in contextual circumstances.

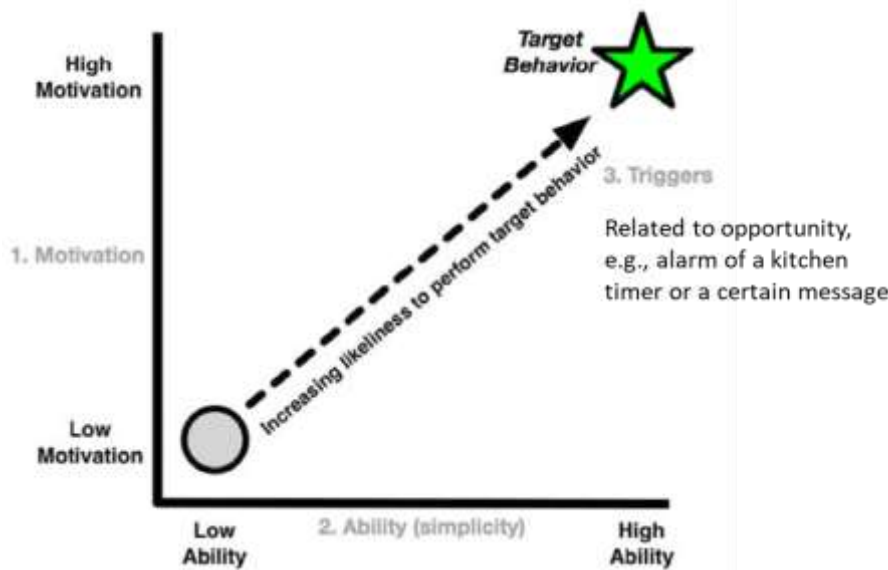


Figure 6: Fogg's behavioral model.

#### 4.8 Contextual Aspects in Energy Consumption

Most people have a positive attitude towards saving energy. Positive attitudes to the behavior however do not provide a clear prediction that the behavior will actually be performed (Ölander & Thøgersen, 1995). (Stern, 2000b) addressed the effect of contextual factors on behavior. Contextual factors can include a variety of external influences such as incentives, needs, physical capabilities and constraints, interpersonal influences, institutional and legal factors, public policy support. Stern implies that when the context effect is small or neutral, the attitude of the user plays a significant role.

On the one hand, when contextual effect is small or neutral, then the expected user behaviours, e.g., turning down heat, turning-off lights etc., can be considered to be “easy”. On the other hand, behaviours that contradict contextual circumstances, e.g., violate current needs or require an investment from the user in terms of effort or comfort loss, they are deemed as “demanding”.

Attitude has little influence on behavior however, when it is strongly influenced by the context. A similar approach is proposed by (Zachrisson & Boks, 2012) for product design. He argues that for the intended behavior to occur, the user has to have a positive or neutral attitude towards the behavior. This influence of context relates to the opportunity-element in the MOA-model, that facilitates certain target behavior. (Gardner et al., 1996) describe that incentives can be very effective in changing behavior. A characteristic of incentives is however, that when they are removed the behavior is often not maintained.

Habits are part of the ability factor in the MOA-model and the Fogg behavior model. Habits strongly determine the behavior of people. Therefore, interventions aimed at changing behavior will have to address habitual behavior as well as intentional behavior. According to (Verplanken & Wood, 2006), to successfully change old and establish new habits, interventions must: “(1) change the context cues that trigger existing habits, (2) establish incentives and intentions that encourage new actions, and (3) promote repetition of new actions in stable circumstances”. This is in the same line as the apparent consensus that behavioral change involves the ‘unfreezing’ of existing behavioral patterns and the elaboration of new alternatives.

Feedback information about energy consumption has proved to be an effective means to enable people to change their energy consumption behavior. The information supports the development of task knowledge, the second element of ability. As the reviews by (Abrahamse et al., 2005) and (Fischer, 2008) show, there have been numerous interventions using feedback to stimulate energy saving. Basic requirements for feedback are that it has to be given frequently, over a long period of time and should enable users to see the consequences of their activities (e.g., the effect of using the washing machine). It is not enough to simply present the feedback information, it should be presented in such a way that it motivates action (Wood & Newborough, 2007). Or as found in (McCalley & Midden, 2002): feedback is only effective when it helps to achieve a goal the user has. Thus, feedback has to be a tool that enables reaching a goal.

In a similar way, tips will only be effective when they help users to fulfil a goal. While feedback only gives information about the results of (energy saving) activities, tips provide knowledge about how to save energy.

#### 4.9 Implicit DR incentives mechanisms, also employing behavioral aspects

There is no doubt that monetary (or pecuniary i.e., virtual rewards measurable or redeemable in money) incentives are very powerful motivators for individuals as it has been proven in a myriad of contexts. Not surprisingly, monetary incentives can have substantial impact upon behavior. However, in many cases the results are disappointing. There are several reasons for this. First, small piece-rate monetary incentives are typical, for example, in the form of rebates on compact fluorescent light bulbs. However, small piece-rate monetary incentives actually decrease desirable behaviors because the reward “crowds out” intrinsic motivations. Non-monetary social incentives such as cooperation, competition, and norms can be more effective than piece-rate monetary incentives (Lepper et al, 2008).

Non-monetary incentives can be strong motivators in some contexts and may be less expensive than the monetary incentive that would be required to generate a similar degree of behavior change. In contexts in which incentives are a potentially cost-effective approach to change behavior, behavioral economics can inform us how to design incentives to make them maximally effective. For example, lottery-like incentives may actually be more motivating than linear monetary rewards because individuals tend to overweight small probabilities and underweight larger probabilities in their decision making. The implication is that if there are two payments of equivalent expected value, a small guaranteed payment and a much larger uncertain amount with a low probability of payment, the latter will be preferred because individuals overweight the low probability of the uncertain pay-out and act as if it has a higher expected value (Madrian, 2014). Furthermore, it was also shown that judiciously applied pecuniary interventions increase the impact of monetary interventions when used in combination. This has increased interest in research in behavioral economics as a guide for policy making (Allcott & Mullainathan, 2010), (DEFRA, 2010), (OFGEM, 2011).

The timing of incentive payments can impact their effectiveness in motivating behavior change, more so than would be implied by standard discounting. If individuals have present bias, temporally proximate incentives will have a much greater impact than those in the future. Another factor that can impact the effectiveness of incentives is whether they are structured such that they are perceived as a gain or as a loss. (Levitt et al., 2012) find that student incentives for test performance are more effective using a loss framing (students are given the reward and then told they will have to give it back if performance is inadequate) than a gain framing (students are told that if exam performance is adequate, they will receive a reward).

Competition as a means of incentive has been effective in incentivizing individuals to reduce energy consumption. (McClelland & Cook, 1980) studied the effect of competition between master-metered residential buildings at the University of Colorado, USA. The buildings, where occupants were not individually metered, were competing on which building would save more electricity. Contestants received information on how to save electricity and feedback on savings of their usage, as well as the usage of the other groups. The winning building received a reward of \$80. The contest groups used 6.6% less electricity than control groups. However, the savings decreased with time, suggesting that the effect of the reward was short-lived. (Pallak & Cummings, 1976) studied whether they could induce reduction in energy consumption through soliciting public commitment. The study was carried out in Iowa City, USA. People who signed a public commitment showed lower rates of increase in gas and electricity use than those who signed a private commitment or those in the control group.

Energy savings can also be motivated by assisting consumers with goal setting. (Becker et al., 1978) gave households a relatively difficult goal (20%) or a relatively easy goal (2%) to reduce electricity use. All households received information on which appliances used more electricity, but only some households received consumption feedback. Only the households that had the difficult goal and received feedback had a significant change in electricity consumption (15% savings). In general, most of the research conducted on non-monetary incentives has involved small samples, and it is not clear if these interventions are scalable. Most of the studies do not monitor interventions for a prolonged period of time, and it is not certain if habits were changed or behaviors eventually returned to pre-intervention norms. Where follow-up studies were conducted, it was typically found that the behavioral changes were not sustained.

Also, there is a number of works on social influence and social recognition. (Friedkin & Jonsen, 1990) describe an approach to the relationship between a network of interpersonal influences and the content of individuals' opinions. Their work starts with the specification of social process rather than social equilibrium. In works from (Richardson and Domingos, 2002) and (Kempe et al., 2003) the problem of influence maximization asks to identify the most influential individuals, whose adoption of a product or an action will

spread maximally in the social network. (Chen, 2008) also studied the spread of influence through a social network, in the model studied by (Kempe et al., 2003). (Rottiers et al., 2009) provided a conceptual framework of how social interactions are affected by the need for social recognition. This study results in an analytical scheme of the actors and factors that affect social recognition games. Also, it reveals the competition that is likely to occur within particular social recognition games.

Towards social pressure, understanding the impact of altruism is an important topic in many research areas beyond computer science, such as economics, psychology and biology. With regards to our project objectives, the experiments designed by (Leider et al., 2009) are important. They show that directed altruism strongly impacts people's behavior in an allocation game. The effect of directed altruism is explored into Lottery Trees (Douceur & Moscibroda, 2007), and Incentive Networks (Lv & Moscibroda, 2015). In both cases, participants are asked to make a contribution towards a global task and receive some sort of reward for it. In Lottery Trees, the winning probability of a person increases with her own contribution and with the contributions of some other people that are connected to her in a social network. The significance for a person of the contributions of other people connected to her depends on their distance from her in her social network. In Incentive Networks, the reward that a person receives depends on her own contribution and the contributions of specific others related to her. Most importantly, the contribution of each person in Incentive Networks is a function of her expected reward and the expected rewards of others related to her. Social impact and networked incentive mechanisms have been studied in great detail in recent years (e.g., (Kleinberg & Raghavan, 2005)).

Moreover, again in the context of peer pressure, it is common knowledge that social media interactions are extremely influential. Social media are ubiquitous, and people consume a lot of time on them. They are habit forming, as it becomes increasingly difficult to separate them from real life. Therefore, social media influence life offline. Businesses are attempting to maximize the user engagement to their content, connect directly to their customers and pass influential messages. Social interaction plays a central role in effectuation processes; however, little is known for implications in effectuation when a business interacts through social media. (Fischer & Reuber, 2011) found that Twitter-based interaction can trigger effectual cognitions, but that high levels of interaction via this medium can lead to effectual churn. Effectual churn is when there is a constant loop between social interaction through Twitter and the reassessment of means and effects achievable without any progression towards those goals. They proposed two factors that moderate the consequences of social interaction through Twitter, namely community orientation (i.e., openness to interacting and helping others) and community norm adherence.

Collectables can be a further direct incentive for players, especially when these are comparable and visible to other players. Curiosity is a big driver when it comes to using collectables as motivational item in a game. Players get motivated by the potential highest item to be collected, this creates a certain addiction to continue playing in order to gain higher rated, and therefore higher valued collectibles. A further motivational part on collectibles is the comparison of collected items of a certain rating / level compared to other players. This behavior can be psychologically followed up to dominance drive in a sense to show other players the own superiority.

#### 4.10 Socially aware incentives

**Definition of social incentive** – American Psychological Association<sup>5</sup>: an inducement to behave in particular approved ways, involving the offer of such interpersonal rewards as acceptance, approval, inclusion, or status.

The presence of social incentives is one of the reasons why people choose to engage in certain prosocial behaviors, such as helping, reciprocity, and cooperation, even when such behaviours contradict their economic self-interest (Benabou & Tirole, 2006; Fehr & Falk, 2002; Dorfman A., 2018). Social incentives can be strong motivators of behaviour, especially in public settings. People act more pro-socially when their behavior is observable by others than when the behaviour is private (e.g., Andreoni & Petrie, 2004; Ariely, Bracha, & Meier, 2009; Dorfman A., 2018).

Offering monetary incentives for socially-valued behaviours may decrease or even eliminate behaviours that are driven by social incentives (i.e., reputation, acceptance, and approval) because the monetary incentive can lead to crowding-out of the social incentives (Benabou & Tirole, 2006; see Titmuss, 1970 for a theoretical model; Dorfman A., 2018)

<sup>5</sup> <https://dictionary.apa.org/social-incentive>

There were many studies performed in the past to evaluate the impact of economic and non-economic incentives, including social incentives. Studies show some contradicting results (Azarova et al., 2020; Buckley et al., 2018; Moser et al., 2016), mostly because of different methodologies, base line data, communication, participants and the whole eco-system as such. In some studies non-economic incentives are considered as environmental and social incentives (Scharnhorst, L., 2021) while both rely on the principle of moral suasion (Ito et al., 2018), with the aim of promoting intrinsic motivation to induce pro-environmental or pro-social behaviour. For this study we focus mostly on social incentives as well as environmental incentives with the impact on social relationships and behaviour.

People perceive not all incentives equal. The rewards that somebody finds motivating might not be enough to inspire another person to react to a call for action. Physiological, social, and cognitive factors can all play a role in what incentives you find motivating.

**Social incentives** could be categorized based on three dimensions. Some individuals prefer to engage with others and value incentives with public recognition and visibility, while others like to be awarded and recognized as important actor, but don't care about broader impact of their actions or don't like to be publicly exposed.

**Three dimensions of social incentives:**

1. **Individuality.** Whether the incentive is reached by the individual person and awarded to individual person only. Example:
  - a. Personal reward (badge) for reaching a number of points in loyalty program or DR program.
  - b. Event organized for closed group of users who commonly reached the target of saving 10 tons of CO<sub>2</sub>.
2. **Public visibility.** Whether the incentive reached is publicly visible (e.g. on social media, web portal, media) or is only known by individual person or closed group. Example:
  - a. Personal reward only visible in my self-care portal. Nobody else knows about it.
  - b. Publicly listed on top 50 contributors chart for saving more than 20 forest trees in 1 year.
3. **Impact.** Whether the incentive reached has broader impact on public, social group, energy poor, digital divided, etc.
  - a. Win a personal ticket for joining a social event.
  - b. When energy community reaches a goal in DR participation the local energy company would give away free 100 simple energy meters to homes in the neighbourhood not having HEMS yet.



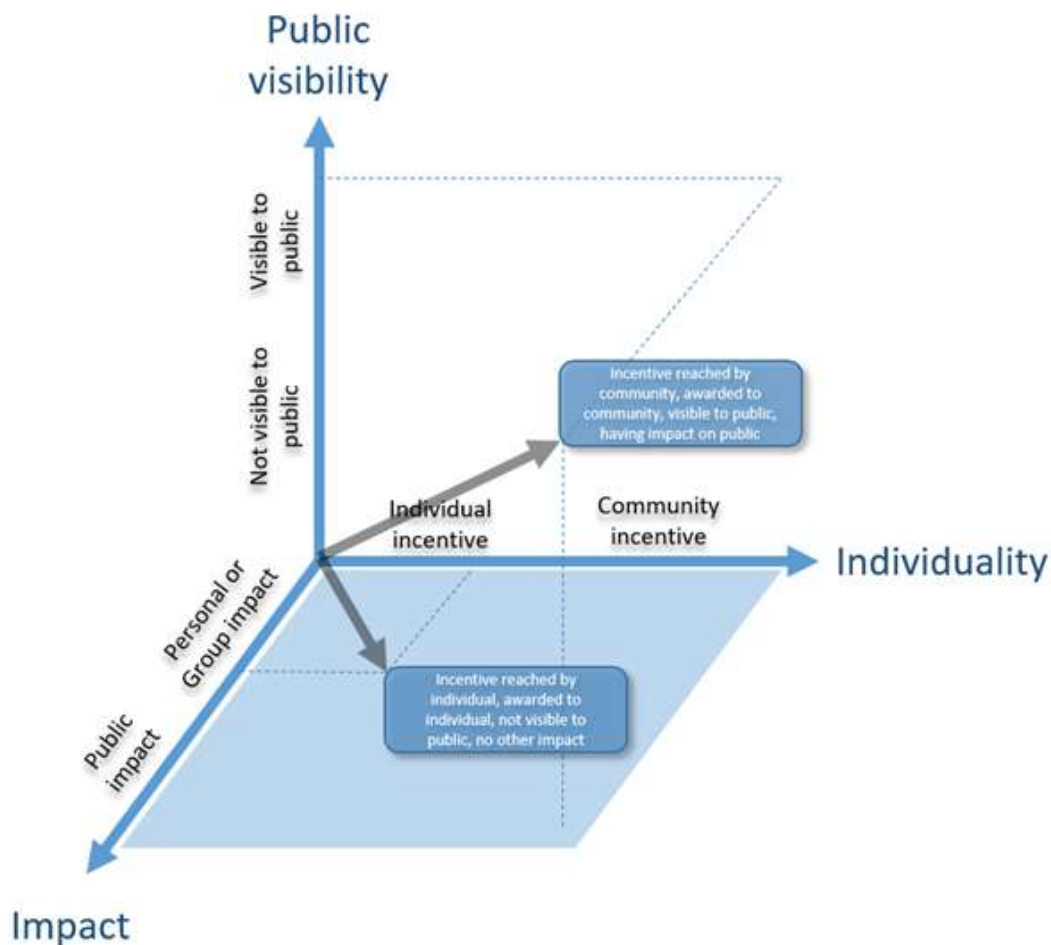


Figure 7: The three dimensions of social incentives.

Focusing on effective DR mechanisms, following are proposed social incentives that could be used as initial input for user engagement and co-creation activities:

Incentives on individual level:

- Potential to introduce within DR mechanisms:
  - Win a ticket or invitation to the ceremony of opening new renewable resources power plant in the neighbourhood (e.g., when the new power plant is built, most engaged users are invited to a ceremony with guided tour, foods and drinks).
  - Win a ticket for a guided tour in one of renewable resources power plant in the neighbourhood (e.g., most active users could win a ticket for a guided tour to visit one of the most modern power plants in the neighbourhood. The guide would physically demonstrate how the power plant works, operates, how they are ensuring security and what is the impact of DR on operation).
  - As an active and recognized participant in DR, receive an invitation to actively participate in designing the next phase of the DR mechanism.
  - Receive points for engagement and participation and possibility to spend them for tangible goods when possible.
  - Receive yearly report for participation and engagement and have the possibility to share it visually on social media.
  - Weekly updating the list of most active participants/consumers in the DR program.
- Potential for sustained engagement with the DR mechanism in the future
  - Receive "Flexy points" for actively participating in DR. Receive badge or recognition when reaching certain number (level) of points.
  - Possibility to share achievement on social media (e.g., FB, Instagram, etc.).
  - Possibility to be promoted (under a nickname) on a top 50 chart.

- o Receive “Flexy points” for actively participating in DR that could be exchanged for buying energy saving products or services.

Incentives on energy community level:

- Potential to introduce within DR mechanisms:
  - o Planting virtual forest with my community based on active participation in DR. Virtual Forest could have small trees, big trees, and rare species. The best foresters are listed. The virtual forest could be at first realized only with numbers (e.g., how many trees are planted), in later phases it could be visualized with advanced graphics.
  - o Compete against other pilots for most active participation.
- Potential for sustained engagement with the DR mechanism in the future
  - o Become an active forum member and advisor to other consumers and participants in DR program. With advisory and active DR participation being nominated for: Rookie, Flexy advisor, Expert.
  - o Based on reaching DR goals of energy community, the cooperative may (co-)finance some local projects or services to overcome digital divide and energy poverty (e.g., financing energy consulting service to build energy efficient buildings in local community).
  - o Based on reaching DR goals of energy community, the cooperative may (co-)finance some local projects in energy saving and renewables.
  - o Real time presentation or simulation of approaching to specific DR goal relevant for my specific energy community (digital twin concept). Real time presentation could lead to more motivation to win. E.g., reduce load in peak hours today for 20%.
  - o When DR call to action arise from a need to accommodate to local renewable power plant production capability, visualize this power plant happy, unhappy, sweaty, etc. based on reactions of consumers participating in DR.
  - o Competition between energy communities in reaching DR goals – gamification (e.g., % of successfully reached DR goals for energy community). The winning community (yearly) could get some financing (or loan) for the local project on energy efficient or renewable resources.



## 5 User engagement and participation enabled by DR incentives

### 5.1 Engagement Mechanisms

The effectiveness of the recommended action, based on the user feedback, has also to do with maximizing the user engagement. According to (PwC, 2016), in order to increase consumer engagement, a power utility should a) simplify complex interactions, creating enjoyable and repeatable experiences, b) personalize interactions, creating proactive experiences and serving customers when and how they prefer, c) create value for the customer and the utility by providing personalized products and services, d) learn the different customer types and use this information to create a more personalized relationship with them, e) provide a good digital experience for customers, and f) maintain and grow customer and wider public trust in its activities by putting non-negotiable safeguards in place on issues such as cybersecurity and use of data.

(Gangale et al., 2013) analyze a number of smart-grid consumer-engagement projects in Europe and reveals that such projects aim at gaining deeper knowledge of consumer behavior, and motivating and empowering consumers to become active energy customers. It also a) reviews the main activities undertaken to obtain the above objectives, b) discusses obstacles to consumer engagement and the strategies adopted by the projects surveyed to tackle them, and c) highlights the need to build consumer trust and to design targeted campaigns taking into consideration different consumer segments.

In (IndEco, 2013), it is argued that utilities can only gain consumers' support and active participation if they create a positive customer experience at all stages of smart grid technology deployment. The report identifies four general success factors that contribute to the smart grid customer experience and increase the likelihood of smart grid project / program success. It also identifies specific strategies within each success factor, supported by examples from ten North American utilities. (BEUC, 2015) mentions that in order to rise the willingness and ability of different consumers to engage with and participate in energy markets, consumer sentiment about a range of issues should be regularly monitored including views on the ease of finding information suitable for carrying out a price comparison; range of tariff offers available through different sales channels; availability of offers suitable for their needs; price comparison processes; the switching process itself; and satisfaction with suppliers' customer service and/or complaints handling performance. According to (Durand, 2015), the secret to engagement lies in tapping consumer motivations and sentiment, and in understanding consumer desires when it comes to smart energy programs and technologies. The author highlights the need for consumer segmentation since, as he mentions, consumers have different energy management desires and needs.

(Orphanedes et al, 2016) illustrate how engagement platforms can be used in energy efficiency programs, and presents guidelines to help program administrators plan, design, implement, and evaluate a modern, integrated, and efficient customer engagement platform. It also shows how advances in big data and tracking systems can support platforms that are technology-enabled, centre on customer needs, leverage psychosocial drivers and data analytics, and employ mechanisms to foster long-term trust and loyalty. In (SGCC, 2013), the engagement strategies and tactics employed by four energy utilities in the U.S. are presented. The authors highlight the following set of successful engagement principles to serve as a resource for all industry stakeholders: 1) Educate customers before deployment, 2) Anticipate and answer questions before customers ask them, 3) Facilitate community engagement, 4) Communicate ways to shift usage off-peak, 5) Deploy user-friendly web portal, 6) Offer user-friendly smart grid enabled technology such as thermostats, and 7) Create authentic customer testimonials.

### 5.2 Gamification

Games can be considered as a specific type of intervention to stimulate behavior. Playing a game allows people to step outside of the ordinary (Huizinga, 1949). They have the characteristic to let people do things differently than normal, to stretch the boundaries of the imaginable.

Games tap into intrinsic motivation. They are inherently engaging. Fogg (Fogg, 2003) argues that intrinsic motivation is powerful in persuading people to perform certain actions. Intrinsic motivation is a type of energizing force that arises directly from an activity or situation. (Malone & Lepper, 1987) defined seven types of intrinsic motivation as: fantasy, curiosity, control, challenge, competition, cooperation and recognition.

There have been some efforts to employ serious games for demand side management in residential settings (Knol & Vries, 2011), (Reeves et al., 2011), (Bourazeri & Pitt, 2013), (Brewer et al., 2013), (Geelen et al., 2014), (Orland et al., 2014). In (Bourazeri & Pitt, 2013), a serious game for smart grids is organized as a virtual world with many user roles and actions, involving direct actions and training for sharing a Medium/Low Voltage transformer among prosumers. A serious game for energy conservation among students is described in (Brewer et al., 2013). The serious-game website and associated game mechanics are provided by the Makahiki system (Lee et al., 2012). Similarly to our setting, no monetary rewards are included in the game; incentives are introduced through competition among consumers for points for energy conservation actions and for participation to online educational and real-world activities. According to (Brewer et al., 2013), energy feedback systems should be actionable, include training and be time-persistent to have long-term effect into energy consumption behavior. Our serious-game model is time-persistent.

Also, the game “Energy Battle” (Geelen et al., 2012), similarly to (Brewer et al., 2013), aimed at encouraging occupants of student-households to save energy by means of competition. In (Johnson et al., 2012), they review multiple energy competitions among university students and identify several pitfalls in their design. Specifically, the use of total energy consumption or (relative) energy-consumption reduction for winner determination is deemed as not adequate when static baseline calculation methods are employed and may be unfair for already “green” consumers.

An online game for improving home energy behavior, named Power House, is proposed in (Reeves, 2011). Its objective is to track activities and assist each member of a virtual family to save energy, while real-world energy behaviors produce particular in-game advantages and disadvantages. An online serious game (“EnerCities”) is presented in (Knol & Vries, 2011) to increase the environmental and energy-related awareness of secondary school students, and to influence their energy-related behaviors. Also, a virtual pet game designed for energy use reduction in a commercial office setting is presented in (Orland et al., 2014), where device-specific energy consumption is reflected in the fitness of virtual pets. There are also a number of studies on gamification in general (Costa et al., 2013), (Mekler et al., 2013), which verify that specific serious-game design elements, such as leaderboards, points and levels, positively influence user participation, engagement and behavioral change.

A generic mathematical framework for the optimization of serious games for energy efficiency has been provided by (Papaioannou et al., 2016). Therein, a simple gain design was employed involving peer pressure and rewards for residential users. This mathematical framework was employed in (Papaioannou & Stamoulis, 2017) for optimizing the parameters of a team-competition game with rewards for energy conservation in work environments. Also, other energy efficiency games, such as “Cool Choices”, “WeSpire”, “Ecoconomy” and “Carbon4Square”, or “Energic” have been used in workplace environments, with very positive results (Cool Choices, 2019; Energic, 2019; Grossberg et al., 2015; WeSpire, 2019).

### 5.3 Eco-Visualization Interfaces

The term eco-visualizations (EV) refer to any kind of interactive interfaces that make user aware of his energy use, and promote sustainable energy-consumption behavior or positive attitudes towards sustainable living (Pierce et al., 2008). Recent advances in EV, smart meters/plugs and sensors provide great opportunities to monitor and display electricity consumption data. Together they provide the potential to give feedback to domestic consumers, commercial building occupants, managers, and other parties, and to encourage energy-saving behaviors. Studies show that mere energy-consumption awareness can provide savings of 5-15% (Darby, 2006).

There is active research in Human Computer Interaction (HCI) on how to create persuasive interfaces to better inform people regarding their choices in everyday activities (Consolvo, 2006), to influence the psychological and behavioral factors motivating their decisions (Mackinlay, 1991), and to motivate positive social changes (Friedman, 2006), (Rosling, 2007). Multiple design strategies for EV exist (Pierce, 2008). Regarding energy conservation, EVs have been proposed to provide contextual, real-time feedback in the form of simple cues or indicators at or near the point of consumption with the goal of guiding behavior (Eco-Eye), (Watson). For encouraging playful engagement and energy-consumption exploration, researchers have begun to design EVs based on ludic activities or activities motivated by curiosity, exploration, and reflection rather than externally defined tasks (Static), (Gustafsson & Gyllenswärd, 2005). Also, there exist some EV approaches that use visual metaphors to connect behavior with carbon impact of individuals and for providing social incentives for energy sustainability by means of an online competition (see Figure 8). However, most commonly EV is employed as an analysis tool. These tools offer more in-depth feedback, allowing users to more deeply explore their consumption patterns (Brun, 2008), (DIY Kyoto).

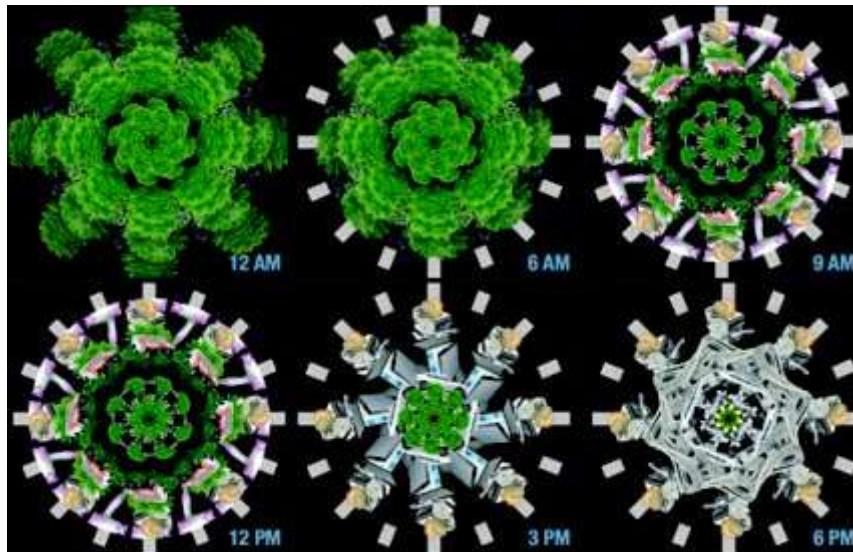


Figure 8: 7000 Oaks and Counting (by (Holmes, 2007)) is an EV that uses artistic and ambient displays to bring attention to the energy consumption.

Less common approaches make use of comparative visualizations to energy consumption using metaphors visualizing the energy consumption of individuals or groups. Car2Go (Gar2Go) uses a digital display using the metaphor of growing trees to visualize the acceleration, braking and regularity of driving (see Figure 9).

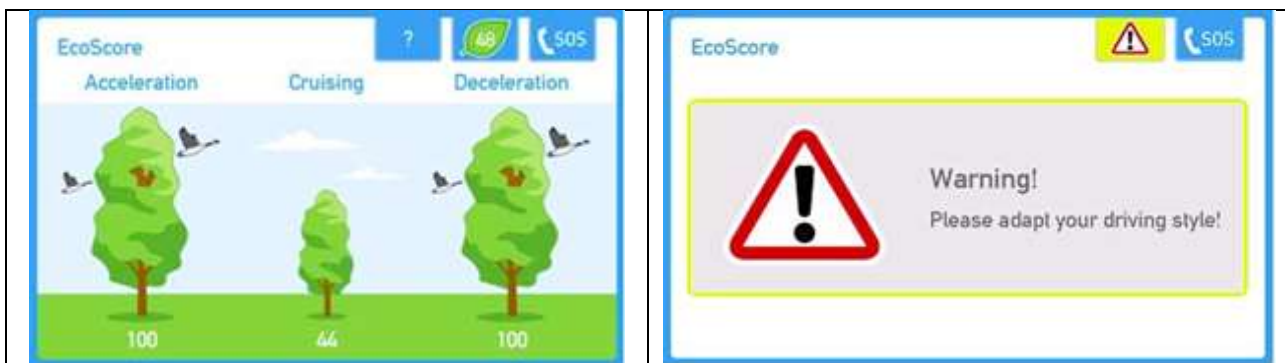


Figure 9: Visualization of driving behavior in adHoc rental car systems (car2go).

The idea is to motivate the user to drive in a moderate way, to prevent accidents and too high fuel consumption while using the rented car. This motivational aspect clearly has a financial benefit, in this case solely for the rental car company, as the player gains no direct benefit from reaching high scores. However, scores in this system have not been shared amongst other drivers, leaving the highest goal to be reaching “100” in the overall rating and therefore only creating a motivation for the driver itself.

Emotional items that motivate users by using the metaphor of a living creature (animal, plant, etc.) keeping it alive or watch it growing, should keep user performance linked to positive effects for the living creature only. The idea of a guilty conscience when this virtually living creature suffers by the player not performing well in a game should be rejected in general (Ascot, 2006).

Motivational items only work, if the user feels emotionally touched by the item itself. If there is no emotional connection, motivational items can become childish and therefore rejected, leading to the opposite, a denial of the intended motivational approach.

## 6 DR incentives applied in practice

### 6.1 Greece

In Greece, there are currently two differentiated DR schemes that are available to final electricity consumers, as follows:

- **Interruptibility Remuneration Scheme:** Interruptibility services provided by eligible High Voltage (HV) and Medium Voltage (MV) installations are compensated by means of the conclusion of auction-based Interruptible Load Agreements with the Greek TSO; it should be noted though that such loads fall off the scope of iFLEX.
- **Residential Off-peak Tariff:** Eligible LV residential consumers can enjoy Time-of-Use (ToU) rates offered by all electricity retailers.

#### Interruptibility Remuneration Scheme (IRS)

Interruptibility Remuneration Scheme (IRS) was initially enacted in 2014 by the European Commission final decision (SA.38711, C(2014) 7374), which foresaw the compensation of certain undertakings located in the Greek interconnected power system that enter into contracts with ADMIE (Greek TSO) to agree to reduce their electricity consumption ("load shedding") for a given period of time and given a stated notice time ("Power Reduction Order") (EC, 2014). As it is common in various European countries (similar schemes have been implemented in seven EU Member States: France, Germany, Ireland, Italy, Poland, Portugal and Spain), industrial users agree with the TSO to temporarily reduce (or "interrupt") their electricity demand to cover imbalances in the supply and off-take of electricity from the network, in accordance with Directive 2009/72/EC (the "Electricity Directive") which states (recital 41) that "*...Member States or, where a Member State has so provided, the regulatory authority, should encourage the development of interruptible supply contracts.*"

In the case of Greece, the need for a regulatory intervention on this matter was primarily due to the lack of an applicable regulatory framework for the participation of demand-response in the day-ahead market or for interruptibility services provided to the TSO: Since suppliers and consumers could not submit bids in the day-ahead market (mandatory pool), the sole possibility for any sort of "participation" by consumers in the day-ahead market would be through the voluntary inclusion of an interruptibility clause in their supply contract. At least twice in the recent past, very large industrial consumers, upon request by Public Power Corporation (PPC) agreed to practically instant load shedding for a limited period of time (approximately one hour), significantly contributing to the security of supply of the electricity system. In fact, the two largest electricity consumers in Greece (an aluminum smelter and a ferronickel producer), accounting for approximately half of the overall annual consumption of HV users, were instructed to hourly shed in total more than 150 MW for more than one consecutive days. Other HV consumers were asked to shed approximately another 150 MW (therefore, about 300 MW in total).

The approval of the aforementioned EC Decision in 2014 was for three years and lapsed in October 2017. In February 2018, the Commission approved the first prolongation of the Greek IRS (SA.48780, C(2018) 604), including a small number of technical modifications, for a further two-year period (Feb 2018 – Feb 2020) (EC, 2018). A second prolongation of the Greek IRS was approved in September 2020 (SA.56103, C(2020) 6658) for a one-year period (Sep 2020 – Sep 2021) (EC, 2020).

In order to be eligible to participate in the current IRS, eligible consumers have to register in the interruptible load register kept by the TSO (one for each product) and should meet the following conditions cumulatively (EC, 2020):

- Their installations must be connected to the Electricity Transmission System (i.e., the High Voltage Network) or the Interconnected Medium Voltage Network.
- The interruptible capacity offered must be at least 2 MW.
- Metering equipment must permit telemetering with at least 15 minutes intervals.

Undertakings connected to the HV Network are typically in the following sectors: Non-Ferrous Metals; Non-Metallic Minerals; Iron and Steel; Lignite Mines; Petroleum Refineries; Cement; Chemicals; and Pumping.



Undertakings connected to the Medium Voltage Network are typically in the following sectors: Non-Ferrous Metals; Non-Metallic Minerals; Iron and Steel; Cement; Paper, Pulp and Printing; Chemical; Food & Beverages; Textiles; Hospitals; Hotels; and Large Commercial Buildings.

Under the IRS, the TSO contracts large energy consumers that are available to reduce their consumption at times of system stress. In exchange for being available to be disconnected (payment for availability), the beneficiaries are remunerated with a fixed payment which is determined by means of three-monthly auctions following the "pay-as-clear" principle. Beneficiaries bid to provide two different services, Type 1 and Type 2. Table 2 presents the characteristics of the two products auctioned under the current Greek IRS.

Further details on the Interruptibility Load Agreement as well as the provision of the related interruptibility services are clarified in the latest Ministerial Decision (MD) 66759/811 (FEK 2997/B/20.07.2020), and are briefly summarized as follows (MD, 2020): Two types of services are to be procured by the TSO, namely Type 1 and Type 2 (see Table 2).

Table 2: Main characteristics of the current Greek IRS.

Product type	Type 1	Type 2
Notice time	5 min	1 min
Duration of each power reduction order	48 hours	1 hour
Maximum number of power reduction orders per month	3	5
Maximum duration of load shedding per year	288 hours	36 hours
Minimum eligible capacity to participate in the auctions	2 MW	
Minimum period between two consecutive power reduction Orders	1 day	5 days
Maximum capacity that can be contracted by the TSO	400 MW	400 MW
Price cap in the auctions	65,000 EUR/MW	45,000 EUR/MW

Both services are intended to support security of the electricity system. The Type 1 service is intended to provide tertiary reserve, while the Type 2 service is intended to provide "fast tertiary" reserve. Within the notice period specified for each service, the beneficiary must reduce its electricity consumption to a level lower than or equal to that specified in the Power Reduction Order. The duration of individual load shedding events (and the cumulative duration of all load shedding events per year) cannot exceed predetermined periods for each beneficiary, depending on the type of service being provided.

The TSO can instruct the contracted consumers to reduce their loads whenever an emergency situation occurs that seriously puts at risk the security of electricity supply. The precise triggering events are laid down in detail in the latest MD 66759/811 (article 5, paragraph 1), which stipulates that the TSO can issue Power Reduction Orders, when one or more of the following occur (EC, 2020):

1. When the ratio of estimated available generation power to the Interconnected System and estimated system load is less than the factor 1.1.
2. When there are exceptional circumstances, like a natural gas crisis, or interruption or drastic restriction of imports of electricity due to the declaration of "force majeure" by neighbouring System Operators.
3. When the operational safety and stability of the system are at risk.
4. When there is a risk for the system stability due to local system problems.
5. When there is a sudden change in the generation of or demand for electricity in the Interconnected System.
6. When it is estimated that the system load coverage is not ensured by the Distributed Units, Contributed Supplementary System Energy Units and Emergency Import Capabilities.
7. When the TSO carries out IRS tests, at least once every six months, on selected energy consumers to check their availability to provide IRS services.

The TSO directly issues Power Reduction Orders to beneficiaries connected to the HV Network. In the case of beneficiaries connected to the MV Network, Power Reduction Orders are issued by the relevant network Operator, following an order by the TSO.

Once a Power Reduction Order has been issued, the beneficiary must not readjust active power to levels exceeding those set out in the Power Reduction Order until it receives a relevant order by the TSO or the validity period set out in the Power Reduction Order expires. The beneficiary must also ensure that the provision of the service cannot cause damage to its facilities or injuries to its employees and give the TSO right of access so that it may verify compliance with Power Reduction Orders.

Compensation to beneficiaries is paid according to their ability to reduce electricity consumption and is specified according to complex mathematical formulas. Compensation is independent of the number or level of Power Reduction Orders that are issued, i.e., beneficiaries are not entitled to compensation for actually reducing active power following a Power Reduction Order by the TSO. In any case, the total financial compensation for any one month cannot exceed a limit of €15 per MWh of electricity consumed by the beneficiary during the month. The cap is intended to prevent possible gaming by bidders and avoid overcompensation by taking into account the actual electricity consumption, i.e., only consumers that were really consuming energy during a month and, therefore, could actually provide the interruptibility service will be reimbursed.

The remuneration is paid to the beneficiaries (large electricity consumers) by the TSO. The cost incurred by the TSO is fully recovered through a specific charge imposed on all producers of electricity in the Greek interconnected system, the Special Charge for Energy Supply Security (SCESS), established in Article 143(B) of Law 4001/2011. The SCESS will vary by generating unit, according to the Equivalent Forced Outage Rate (EFOR) of each technology for the period 2010-2019.

Failure to comply with a Power Reduction Order from the TSO will result in penalties, intended to mitigate the risk that consumers might be tempted to proceed with the conclusion of an interruptibility contract, while being unable (or unwilling) to actually provide the service. For a first compliance failure, the penalty will be proportional to the total remuneration for the entire duration of the contract (but no more than 110% of the total contractual payment they are entitled to), according to a mathematical formula set out in the Ministerial Decision. In case of a second failure to comply, the contract with the TSO is automatically terminated and the consumer is required: (a) to return all payments already received; and (b) to pay in addition a penalty equal to 20% of the total remuneration deriving from the contract had it not been terminated.

## Residential Off-Peak Tariff

Regarding the second commercially available DR scheme, it is first noted that almost all LV customers in Greece are still equipped with conventional electromechanical metering infrastructure allowing only for aggregated electricity consumption data reading. Monthly or four-monthly time intervals are mostly used by the electricity retailers to invoice their LV customers for their aggregated real consumption.

In this context, there are Time-of-Use (ToU) rates offered by all electricity retailers to eligible LV residential consumers only (Residential Off-Peak Tariff). A residential consumer who is interested to become eligible for and enjoy such a service can ask Hellenic Distribution Network Operator (HEDNO) for the installation of a time-based meter in his premises, that is a conventional meter that registers the aggregated electricity consumption in two distinct time periods separately, namely the time period of regular electricity rate (day zone) and the time period of discounted electricity rate (night zone). Electricity retailers are free to set the specific tariffs (in €/kWh) for each time period (day/night zone).

The timetable of the aforementioned Residential Off-Peak Tariff is defined by HEDNO and is as follows:

### 1. *Segmented Timetable*

- Winter period (1st of November until 30th of April)
  - 02:00-08:00 and 15:00-17:00, for residential consumers located in Mainland and the Interconnected Islands.
  - 02:00-08:00 and 15:30-17:30, for residential consumers located in the Non-Interconnected Islands with segmented timetable
- Summer period (1st of May until 31st of October)
  - 23:00-07:00, for all residential electricity consumers

### 2. *Continuous Timetable\**

- All year round: 23:00-07:00

*\* The Residential Night Tariff with continuous timetable all year round is no longer provided for new electricity consumers. It is applied only to residential customers who already use the reduced night tariff before 1998 (provided that they did not ask for its change) or live in certain geographical areas of the country where appropriate technical infrastructure of the Distribution Network does not exist, that is, Audio Frequency Remote Control system is not available.*

Besides the aforementioned two commercially available DR schemes, currently no IT infrastructure that would allow for unidirectional or bidirectional communication between HEDNO/Retailers and the end-consumers and, in turn, for the massive deployment of more sophisticated DR programs is available. In the near future, HEDNO is planning to proceed with the replacement of the existing 7,5 million conventional electricity meters with smart meters. This large-scale project is expected to allow for real-time access to massive electricity consumption data, further aiming at the extended deployment of DR programs as well as the strong engagement of as many as possible end-consumers towards more efficient use of energy.

## 6.2 Slovenia

In Slovenia currently fixed tariffs are used for small businesses and physical customers. One- or two-tariff billing system is supported. The second one aims at shifting consumers' energy consumption into periods when the network load is smaller. Price of electricity and network fee are higher between 6:00 to 22:00 during workdays, otherwise the prices are lower. The electricity price during hours with the lower fee is roughly 55% of the higher price and the network fee for households is 76% of the higher price network fee. The fees are not changed really dynamically in time, they can be fixed for several months.

With a new regulation a possibility of dynamic tariffing has been introduced in Slovenia. The regulation first phase intention is to allow to offer a conscious buyer lower market price on account of their flexibility. The electricity prices could be changed even during a day. For example, the buyer could be signalled a day in advance that the price will be lower during evening hours from 21:00 to 24:00. The buyer could use the specified time frame to increase his consumption by charging his electric vehicle, wash or dry laundry, etc. Example of dynamic tariff implementation can be found abroad, for example Octopus Energy<sup>6</sup> already offers dynamic prices in Great Britain.

For network fees the Energy Agency in the Slovenian energy market<sup>7</sup> has prepared a regulation, a network act that enables their dynamic charging. The iFLEX project partners, namely Elektro Celje (ELE), Smart Com (SCOM) and Institute Jozef Stefan (JSI) participate in the project Use it Wisely (UiW)<sup>8</sup>. The UiW uses some of the dynamic charging possibilities of the network act, namely PKKT, positive critical peak tariff, and NKKT, negative critical peak tariff. At the time of the PKKT the network fee is approximately 10x higher and at the time of the NKKT 66% lower than ordinary network tariff. There are 3650 hours of NKKT and 30 to 100 hours of PKKT available in a year for a distribution grid using dynamic tariffs.

The Energy Agency is in this year working on a project on new tariff system<sup>9</sup> which will be available in the next period 2021-2024. The new tariffs are of high interest for the iFLEX Slovenian partners and the iFLEX project as well. The network fees will be different according to time of day. The day will be split into time blocks with a pre-defined fee according to network conditions in the time frame. The end users will have a possibility to announce their consumption during the blocks. They will pay reserved price for the announced consumption and higher price for the consumption beyond the announced one. Since the project is ongoing, more information on all possibilities will be available at the end of this project.

## 6.3 Finland

In Finland, DR activities are relevant both for the power grid and for the district heating (DH) network. The monetary incentives for DR activities in the power grid can be originated from two different sources. The first source is dynamic prices (energy and grid tariff); while the second one is the electricity market, including intraday, balancing, and reserve market. The latter one needs aggregators to form DR programs and compensate customer accordingly. For district heating, the main source for incentives is reduction of peak loads at a building level. Additionally, some DH companies pilot DR programs where flexibility signals are sent to buildings and consumers and compensated for their flexibility. Moreover, through electrification of space heating, cost-optimization across DH and electricity is also an interesting incentive and source for flexibility in the near future.

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<sup>6</sup> <https://octopus.energy/agile/>

<sup>7</sup> <https://agen-rs.si/web/en>

<sup>8</sup> <https://www.elektro-celje.si/si/uporabljaipametno>

<sup>9</sup> [https://www.agen-rs.si/posvetovanja/-/asset\\_publisher/M2GdU2jRtCxV/content/vzpostavitev-trga-s-proznostjo-aktivnega-odjema-v-sloveniji-izhodi-1](https://www.agen-rs.si/posvetovanja/-/asset_publisher/M2GdU2jRtCxV/content/vzpostavitev-trga-s-proznostjo-aktivnega-odjema-v-sloveniji-izhodi-1)

### 6.3.1 Dynamic energy and grid tariff prices

As mentioned in D5.1, almost all of 3.7 million consumption/production points in the electrical system are equipped with smart meters, which are measuring the energy exchange at least on an hourly resolution. The validated hourly metering data is available the next day for the customer, energy retailer, balance settlement and other relevant operators. Soon, using Datahub, as a central information exchange system, this process is accelerated and improved.

Currently, the price of electricity for end-users consists of three parts: the price of electrical energy, the price of the electricity network service (grid tariff), and taxes. Fig.14 in D5.1 shows two examples of approximate shares of energy bills for a normal house in a city area and a rural area. It can be seen that the energy cost (plus the corresponding value-added tax (VAT)) has only 36% - 45% of total electricity cost. The network service is responsible for 34% - 47% of the total electricity cost. The rest of the cost comes from the energy tax (17% - 21%). It is worth mentioning that since VAT is proportional to total costs, it is excluded from the tax and considered as part of the energy cost, grid tariff, and energy tax.

While the energy tax is a fixed amount and DR cannot change it, end-users can reduce the energy bill by shifting their consumption if they use dynamic energy prices and variable grid tariff. Like many deregulated electricity markets, end-users are free to choose the electricity energy provider from more than 70 energy retailers, working in Finland. However, end-users are obligated to use the network services provided by their local DSO.

Almost all the electricity retailers suggest a contract with an hourly-based price, this dynamic energy price is usually the wholesale market price plus a small margin, e.g., 0.2-0.3 Euro cents per kWh. This type of contract is very useful for the customers who want to manage their consumptions and supports naturally demand response activities. However, due to the complexity of the price structure for the public and/or a lower profit margin for the retail company, it is not a popular scheme and only about 10% of customers currently choose this kind of energy contract.

The variety of the grid tariffs for DSO and TSO services is very limited. The grid tariff needs to be similar for all customers in one DSO region, according to the regulation. Therefore, DSOs cannot directly change the grid tariff of some end-users according to the grid congestion. However, they can have dynamic tariffs according to time of use, and providing a similar opportunity for all their customers. Currently, the dynamic grid tariff does not have an hourly resolution. Usually, a DSO has different grid tariff for day and night. For example, the current grid tariff for the DSO which provides services for the Finnish demonstration site in Kerava includes 2,7 Euro cent/kWh in the daytime and 1,5 Euro cent /kWh for night-time (from 10 at night till 7 in the morning).

In district heating, the energy fee is typically seasonal. The price is higher during the winter and lower during the summer. Since the price does not fluctuate during the day, there is no real opportunity for flexibility management with the energy fee. However, with sector integration (i.e., with heat pumps and DH) it is possible to optimize flexibility across DH and electricity assuming that spot prices are used for electricity. In addition to the energy fee, DH has a power fee (also known as basic fee), which provides some incentives for flexibility management. There are no universal rules for calculation of the power fee. Some companies use average power calculated over one to 24 hours, while others use flow of the water as a measure instead of the power (the reason is that they want to motivate consumers to lower the temperature of the DH return pipe as much as possible to increase overall efficiency of the system). For large apartment buildings (~80 apartments) the power fee is roughly 3-4 k€/year in Helsinki area. Thus, reduction of peak loads by 10- 30%, would reduce the yearly cost with 300-1.200 € at the building level.

### 6.3.2 Balancing and reserve market

The structure of the Finnish energy market is explained in Section 3.4.4 of D5.1. A significant share of electrical energy is traded in the day-ahead market, which determines the hourly price for the energy in the afternoon of a day before the delivery day, using the margin price principle in the merit-order list. Another option for trading the electrical energy is the intraday market, which allows trading the electricity until the delivery hours, but the clearing method is based on the immediate match finding and pay as bid. In other words, there is no merit order listing.

Participating in the market is not possible for most of the end-users, such as residential or small/medium-sized business. Therefore, there needs to be another party to aggregate their consumption, production, or flexibilities. As one option, an aggregator can form the up-regulation or down-regulation of its customer for a specific hour as a purchasing offer or selling bid in the intraday market. The main advantage of participating



in the intraday market is that the market has less complexity in comparison to the balancing and reserve market. The aggregator can optimize (i) when to put the offer or bid in the market and (ii) how long before delivery time to cancel the bid or offer if there is no matching request. This freedom helps to aggregate the loads that have a slow control process or unpredictable behaviour far ahead of time. However, since there is no payment for the capacity, the potential of flexible loads, the compensation will be just for the energy, the total annual income would be minor in comparison to capacity market in ancillary services, such as balancing and reserve market.

However, participating in the balancing and reserve market is more complicated. This market aims to keep electricity production equal to electricity consumption at all times. In this regard, the transmission system operator of Finland, Fingrid, procures different flexibility products in the reserve and balancing market with a wide range of technical requirements. There are several technical requirements for participating in the balancing and reserve market, such as minimum bid size, measurement or communication requirement, controllability of loads, activation times, and prequalification process. The system operator wants to be sure about the quality and reliability of the resource. Therefore, they provide a prequalification process for each resource and provider. In addition, they need to agree on the method to measure/predict the baseline consumption/production. The baseline value is required to measure the flexibility of customers. However, calculating the baseline consumption of an aggregated residential area may not be a straightforward process. Figure 10 classifies the main flexibility products in Fingrid’s reserve and balancing market according to their activation time.

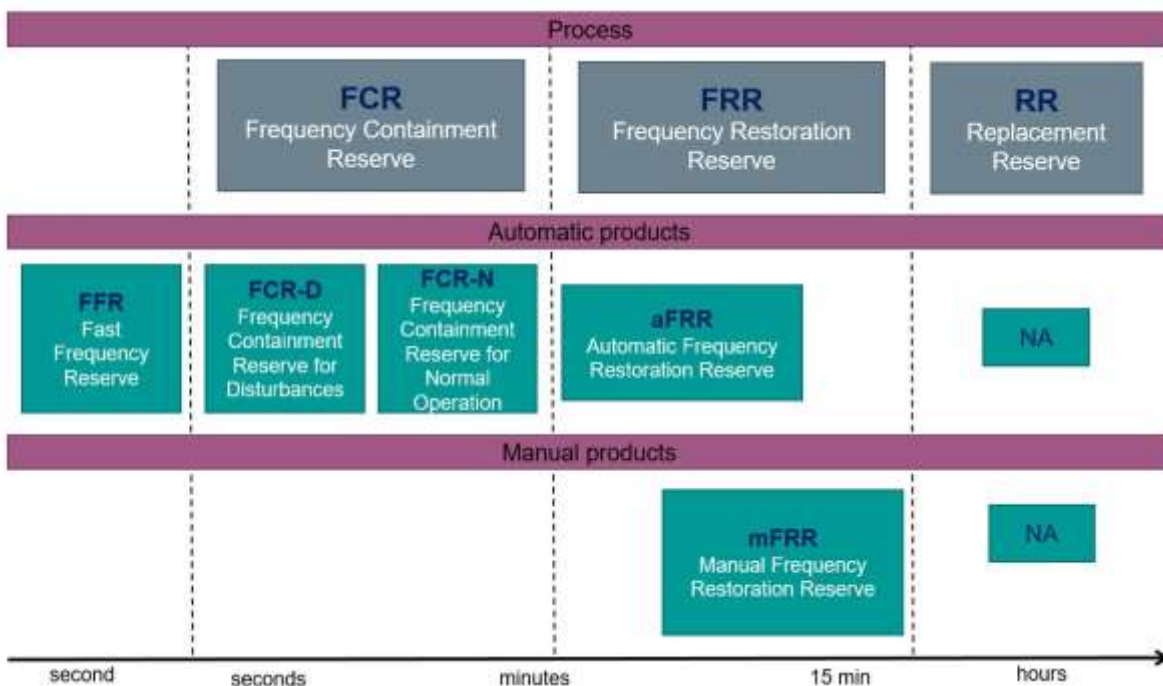


Figure 10: The main flexibility products in Fingrid’s reserve and balancing market, classified based on activating time.

Most of the balancing and reserve product have both capacity and energy market. In the capacity market, the flexibility provider sells the capacity or the potential of providing the service. It means they got paid just being ready to provide the flexibility (up or down-regulation energy), whenever it is needed. The system operator, Fingrid, paid the capacity fee to make sure that the availability of reserve resources. The flexibility provider will be compensated for the provided energy according to the regulation market price. However, if the flexibility provider cannot provide according to the capacity they sold, they get a penalty. The amount of the energy capacity remuneration and the penalty depends on the product.

The participants in the capacity market need to submit their bids for a period of time, long in advance of the delivery time. For example, in the FCR market, as explained in D5.1, there is a yearly and day-ahead market. In the yearly ahead market, the provider needs to bid for the next year, with hourly resolution. For the mFRR product, the capacity bid includes a fixed capacity for one week, which need to be submitted 4 days before

starting the week. Although the capacity market provides an opportunity to increase the income of the flexibility provider, it may decrease the income or even leads to some loss, due to penalty. In other words, in order to participate in the capacity market, an accurate prediction of the flexibility potential is a must.

The energy compensation of all these balancing and reserve products is set based on the balancing carried out in the Nordic balancing energy markets. In the Nordic balancing energy markets, both up-regulating and down-regulating energy prices are set for each operational hour. The up-regulating price is the price of the most expensive up-regulating energy bid used, however at least the price in the day-ahead price (for Finnish area in Nord Pool (Elsport FIN)). The down-regulating price is the price of the cheapest down-regulating energy bid used, however, no more than the price in the Finnish price area in Nord Pool (Elsport FIN). Balancing energy prices are primarily published on Nord Pool's website no later than two hours after the operational hour in question.

It is worth mentioning that the revenue results from aggregated flexibility need to be divided between the aggregator and participants after reducing all the related cost, according to some pre-agreed plan.

## 6.4 Rest of EU / World

Residential demand response in Europe is still at the early stage and a fully transparent value of flexibility for the consumer is yet to mature as in many cases, flexibility is bundled through the retailer (Bertoldi et al, 2016), mainly as time-of-use prices which are more or less dynamic.

In the US, residential demand response is more advanced in terms of explicitly addressing adjustment of energy usage, with programs offered not only by the retailer but also by independent aggregators<sup>10</sup>

An initial walkthrough of existing demand response solutions reveals the following incentives, which address individual as well as collective gains, often combined for greater appeal:

### Individual incentives

- Economic: Save or earn money by adjusting energy consumption, get paid for the electricity you export<sup>11</sup>, get compensation for sharing kwh<sup>12</sup>
- Empowerment: Take the control back e.g., through provision of knowledge about one's energy system<sup>13</sup>, evidence of DR participation and ability to opt out<sup>14</sup>
- Efficiency: Be smarter and maximise your home efficiency
- Independence: Achieve self-consumption and become energy independent and self-sustainable (not understood as off-grid but for example based on providing a small share of storage as a buffer for the public power grid)

### Collective incentives

- Environment: Contribute to a cleaner energy transition, get moral satisfaction, help balance the grid without 'dirty' emissions<sup>15</sup>.
- Secure supply: Prevent power interruptions, avoid the cost of expanding the power grid, help conserve the power grid<sup>16</sup>.
- Community feeling: Be part of and contribute to the community by sharing home produced surplus energy with other members.

The predominant incentives are economic with focus on the individual benefits but often in the framework of environmental and collective incentives, emphasizing not only the personal benefits but also advocating the collective aim of cleaner energy through uptake of RES and reduction of carbon footprint as well as grid stability. Some companies emphasize the environmental aspect further (<https://myenergi.com>, <https://www.ohmconnect.com/about-us>) for example through guarantees of 100% green electricity

<sup>10</sup> [https://www.pge.com/en\\_US/residential/save-energy-money/savings-solutions-and-rebates/demand-response/demand-response.page](https://www.pge.com/en_US/residential/save-energy-money/savings-solutions-and-rebates/demand-response/demand-response.page)

<sup>11</sup> <https://octopus.energy/outgoing/>

<sup>12</sup> <https://sonnengroup.com/sonnencommunity/>

<sup>13</sup> <https://myenergi.com/>

<sup>14</sup> <https://tiko.ch/page/freqaq/201/>

<sup>15</sup> <https://innovation.engie.com/en/news/news/new-energies/tiko-energy-aggregation-for-householders/12868>

<sup>16</sup> <https://www.ohmconnect.com/>

(<https://octopus.energy/>) or by enabling the use of energy when it is cleanest (OhmConnect). Often the community feeling is addressed or the security of supply. However, in most cases, the individual incentives take precedence:

- 'Power for the people: We're doing energy better — for you and for the environment' (<https://octopus.energy/about-us/>).
- 'Self-consumption always has the highest priority over network stabilization' (<https://tiko.ch/page/freqaq/307/>),
- 'A household will save 100 % of its energy costs. At the same time, the general public also profits from this technology because it negates the need to expand the public power grid' (<https://sonnengroup.com/sonnencommunity/>).

## 6.5 Lessons Learnt

Overall, only a small number of DR offerings have been commercially provided in the iFLEX pilot countries and more generally in the world. Predominantly, these DR programs involve economic incentives, which have mostly experienced moderately adequate response from electricity consumers, despite their relatively small economic impact. DR schemes involving a combination including both economic and not economic incentives are currently under study and initial commercial deployment. Collective goal setting has been employed in certain DR schemes, but individual goal setting is always considered to take precedence. So far, large-scale service disruption or dynamic service disruption based on DR signals have not been considered for residential consumers (only for industrial ones), while residential consumers mostly schedule their electricity consumption on the basis of static pricing signals applicable in a long-term basis (e.g., in Greece) or one-day ahead (e.g., Slovenia), as opposed to dynamically receiving DR signals and self-optimizing in real-time. Therefore, in the pilot studies of iFlex, we mostly assess innovative DR schemes that have not been commercially deployed for the purposes of attaining and harnessing flexibility, and combine financial and not economic DR incentives.

## 7 Initial proposition for DR incentives mechanisms in iFLEX pilots

### 7.1 Greece

In the Greek pilot, relays for switching off the water heater are installed at the households. The residential consumers are provided the option to participate or not. If they participate, upon a DR event for flexibility purposes, users are notified not to use their water heaters and relays are switched off for a specific period in the future. Potential flexibility that can be provided depends on user activity schedule and it can be estimated based on baseline data and user preferences. The flexibility obtained, i.e., the electricity consumption reduction, is to be offered to a RES aggregator for balancing purposes via the retailer (HERON) acting as a DR aggregator. The initial plan is that the residential consumers are provided with the following incentives for participating in the DR program:

- Rewards, by means of tokens or points that are redeemable, e.g., employed as tickets in lottery schemes for some prizes, providing access to special offers, translated into special discounts for electricity consumption, etc.
- Environmental awareness, i.e., based on estimated Kg of CO<sub>2</sub> offsets due to user participation
- Peer pressure, i.e., percentile where the user belongs to based on how well the user fares in environmental friendliness as compared to others in the pilot (or even in a specific geographical location of the Greek pilot)
- User empowerment, by means of detailed analysis of electricity consumption and associated costs, so that the user feels more in control in that respect.

The electricity consumption related to water heaters is related to the shower activity, which can be shifted in time and even shortened/lengthened. Based on the aforementioned incentives and the discomfort involved into disrupting scheduled showering activity, after each DR event, the users provide feedback on their satisfaction from their participation in the DR event.

The DR designer aims to select the rewards so as to maximize the participation rate of the residential consumers within the available budget. At the same time, the DR designer could aim

- i. to maximize the expected flexibility to be obtained at the DR event within the available budget;
- ii. to obtain the needed flexibility in expectation at the minimum budget.

Thus, assuming that electricity consumption reduction by consumer  $i$  is  $x_i^t$  in the specific time slot  $t$  of the DR event, and a probability  $p_i$  that the user participates based on the incentives provided and the arising discomfort, then the DR designer aims to select the rewards, so as to achieve one of the aforementioned objectives. The user feedback and prior history of DR participation are employed for calculating the probability that certain incentives can be acceptable by specific users. The aforementioned optimization problems are formulated in the Appendix on the basis of a model for DR targeting and calculation of incentives under uncertainty.

### 7.2 Slovenia

In the Slovenian pilot, HEMSs are going to be installed at prosumer/consumer premises. HEMS will provide readings from individual devices at residential premises in the future, and readings from sensors for comfort (temperature, humidity), heat pumps and boilers. In the case of prosumers, PVs will generate electricity that can be injected into the grid or consumed locally, since currently there is no electricity storage capability. The customer pays only for the total net power consumption in the billing period. However, no selling of electricity actually occurs.

In this pilot, flexibility is expected to be provided based on DR signals that are practically high network tariffs for specific hours announced one day ahead. These network tariffs could potentially be combined with dynamic retail tariffs in the flexibility events. The users are expected to change their electricity-consumption schedules in response to these higher tariffs, so as to minimize their electricity bill, and thus offer flexibility.

In addition, messages are to be sent to users for energy consumption feedback (i.e., energy advice) and encouragement for reacting upon these signals. The users practically cannot opt-out. However, the users are

free to choose their own self-optimizing way to react to DR signals, by adjusting or not their electricity consumption schedule accordingly. Hence, while they cannot declare opting-out, they may opt out in practice by not responding to DR signals. Contrary to the Greek pilot, Slovenian users will be able to choose which activities involving electricity consumption to shift in time or cancel. The flexibility offer (negative or positive) can be estimated based on current load profiles of the prosumers in this pilot.

Apart from the energy-cost incentives and the energy advice/encouragement messages, additional incentives can be employed, similarly to the Greek pilot. Therefore, the complete list of incentive schemes to be employed in the Slovenian pilot are as follows:

- High electricity tariffs for specific time periods of flexibility need, similarly to a TOU DR scheme.
- Environmental awareness, i.e., based on estimated Kg of CO<sub>2</sub> offsets due to user participation
- Peer pressure, i.e., percentile where the user belongs to based on how well the user fares in environmental friendliness as compared to others in the pilot (or even in a specific geographical location of the Slovenian pilot)
- User empowerment, by means of detailed analysis of electricity consumption and associated costs, so that the user feels more in control in that respect.
- Financial rewards, given the value of the flexibility collectively provided, e.g., proportional to the contribution of each consumer to the flexibility offering.

Assuming non-completely rational and heterogeneous users, and diverge contextual drivers and comfort preferences, users are expected to react differently in terms of adjusting their electricity consumption to the incentives provided. The Slovenian users may use explicit feedback to express their satisfaction and/or discomfort from the incentives provided and may choose to react on the DR signals provided or not (thus providing implicit feedback on their satisfaction from the incentives provided).

Again, similarly to the Greek pilot, the DR designer may assign a probability to each user to participate. However, in this case, also the amount of flexibility that is provided by a participating user is *uncertain*, but it is upper bounded (i.e., shiftable, interruptible, reducible activities in the specific time slot of the DR event).

Moreover, the power generation forecast from the PVs, should be taken into account by customers to determine the amount of power consumption to be rescheduled during the flexibility event.

Similarly to the Greek pilot, the DR designer may seek one of the following goals:

- to maximize the expected flexibility to be obtained at the DR event within the available budget;
- to obtain the needed flexibility in expectation at the minimum budget.

### 7.3 Finland

This pilot will investigate the provision of flexibility by exploiting the thermal mass of the buildings. In the building employed in the Finnish pilot, district heating is combined with exhaust air pumps (that consume electricity) at the building level to heat the apartments of the residents. While several complex alternatives do exist for providing flexibility, e.g., determine hot water setpoint temperature for district heating, the initial scheme is to provide flexibility simply by turning off the district heating (i.e., hot water supply) for the building for a short period of time. The assumption is that indoor temperature will not drop very fast within the flexibility period due to the thermal mass of the building. The building occupants cannot opt out from this flexibility provision, but (a) they are provided reassurances that the indoor temperature will not drop below the lowest temperature dictated by the regulation, and (b) they will be able to provide feedback on their potential discomfort. The feedback will be mostly anonymous with very few residents belonging in a control group only able to provide named feedback.

The indoor temperature is going to be monitored to make sure that it is above the legally acceptable lower bound. If the majority of users in the building are dissatisfied with the indoor temperature or the latter falls below its lowest acceptable bound, then the flexibility period is terminated (even before its prespecified duration).



The primary objective of the aforementioned DR mechanism is to exploit energy flexibility, while not affecting user comfort at all or if affected (even insignificantly) be properly compensated by means of incentives (not necessarily monetary). The building residents are supposed not to react (i.e., not provide feedback or provide positive feedback), if their comfort is not violated. Moreover, they are not supposed to respond by altering their electricity consumption schedules within the period of the DR event in any way. In fact, though, such a scenario is far from impossible, for example, postponing energy-consuming activities for later (due to colder indoor environment), choosing to do some unscheduled cooking (to exploit the extra heating produced), etc., during the DR event. In the extreme case, some residents could even opt to use individual exhaust air heating devices.

Therefore, some incentive schemes should be employed to compensate users against their potential discomfort and disincentivize potential energy consumption misbehaviours. Hence, the success of the flexibility event should be connected to the incentives provided to the end users. The following incentives can be employed:

- **Fixed Rewards:** Vouchers or tokens can be used for compensation or lottery tickets for rewards for participating residents that do not provide negative feedback throughout the duration of the DR event. This incentive can be equal for all satisfied users.
- **Variable Rewards:** Decide on the amount of reward and the duration of the heating interruption, so that majority of users are happy. In this incentive scheme, each user receives more reward the later she provides any discomfort feedback. When the majority of users are dissatisfied or the DR event ends, a fixed total amount of rewards is shared to users proportionally to their tolerance time before their negative feedback has been submitted (if any), provided that the DR event succeeds, i.e., it produces some useful amount of flexibility. For those users that did not submit any feedback, the duration of the DR event is assumed to be their tolerance time. In economic terms, the situation resembles a public goods game, where multiple users (each one independently) choose to contribute or not some costly effort for its creation and they all receive a higher value in return if the public good gets constructed. Two more variations can be considered in this incentive scheme: (i) Exclude from rewards users that provided negative feedback before a certain lowest time threshold, even if the DR is successful; (ii) Reward only the top percentage (e.g., 20%) of users in terms of tolerance. The latter incentive scheme resembles a sealed-bid reverse-auction where users bid for higher discomfort-tolerance, in exchange for higher rewards. The aforementioned rewards can be a portion of the value of flexibility gains.
- **Peer Pressure:** Before the DR event a collective flexibility goal is announced. The overall acceptance rate is announced and the more negative feedback received, the lower are the chances to reach the flexibility goal. The intuition here is that if dissatisfaction ratio is close but below 50%, then the users that have not provided negative feedback yet will be under more pressure to act so, in order to avoid taking personally the blame for failing the flexibility goal (although this information always remains private). Note that anonymous feedback is not only easier to implement, but it is also preferable in terms of incentives, because it does not socially stigmatize any user. We do not follow punishment concepts, because psychology research has shown that these can produce negative emotions, such as fear and anger, and can overall lead to passive behaviour. Approaches based on adhering to social norms (as is now proposed) or follow the lead (to be investigated in the future) create some positive reinforcements and are thus preferable.
- **Bill Savings:** The residents are sharing the savings on their district heating bill. Again, here, the bill savings can be shared only among the contributing users or the considerably contributing users (in terms of tolerance time) or among the top contributing users amounting to a prespecified percentage.

Individual electricity consumption metering is still not possible, but this may be feasible in the future in this pilot. Then, the aforementioned incentive schemes will also take into account any rebound effects from the DR event into electricity consumption, before, during, and especially after the DR event. Moreover, individual electricity consumption monitoring will enable incentive schemes against electricity consumption misbehaviors, such as those mentioned above.



## 7.4 Requirements imposed to iFLEX architecture and assistant

The following requirements have arisen from the preliminary incentive mechanisms for the iFlex architecture and assistant, they are presented in the JIRA format adopted for requirements engineering in the iFLEX project:

### **UI for the user to participate or not to DR signal**

This requirement has been already reported in iFLEX D4.4 as IF-52. Its description is also repeated here for convenience and completeness reasons. The iFlex assistant A&M interface must be able to communicate a signal indicating acceptance or rejection of participation in an upcoming explicit DR action, as provided by the Automated Flexibility Manager (automated operation) or the end-user interface (manual operation).

### **Access to personalized feedback on user satisfaction from participating to a DR event**

#### **[IF-73] Access to individual feedback on user satisfaction from the service**

<b>Type:</b>	Functional
<b>Reporter:</b>	<a href="#">Thanasis Papaioannou</a>
<b>Labels:</b>	A&M

<b>Rationale:</b>	The perception of the incentive mechanisms by the user is important to be available in a detailed format per DR event, at the individual level if available, or on the aggregate otherwise.
<b>Source:</b>	D5.2
<b>Pilot Finland:</b>	Phase two
<b>Pilot Greece:</b>	Phase two
<b>Pilot Slovenia:</b>	Phase two

#### **Description**

The iFlex assistant A&M interface should make available to other system components (e.g., DRMS) detailed user feedback on user satisfaction from the incentives provided in the different DR signals/events. This feedback will be employed by the incentive-mechanism design algorithm to assess the effectiveness of the incentive mechanisms and to fine-tune the process.

### **UI to submit feedback on user satisfaction from participating to a DR event**

#### **[IF-74] User Feedback on Satisfaction from DR/Flexibility Event**

<b>Type:</b>	Functional
<b>Reporter:</b>	<a href="#">Thanasis Papaioannou</a>
<b>Labels:</b>	UI

<b>Rationale:</b>	Allow the user to reflect on her/his overall satisfaction from DR events.
<b>Source:</b>	D5.2
<b>Pilot Finland:</b>	Phase two
<b>Pilot Greece:</b>	Phase two
<b>Pilot Slovenia:</b>	Phase two

#### **Description**

The users should be able to provide their feedback regarding their overall satisfaction from their participation in a DR event. This feedback takes into account multi-faceted incentives (e.g., rewards, peer pressure, etc.) provided to users for their participation to a DR event and their relation to the user discomfort, to determine a positive, a neutral or a negative perception on the DR event. This perception

influences the probability that the user will participate in future DR events. This feedback may be visualized with 5-star Likert scale.

### **Access to personalized DR participation / actuation**

#### **[IF-75] Access to individual data on user participation in DR events**

<b>Type:</b>	Functional
<b>Reporter:</b>	<a href="#">Thanasis Papaioannou</a>
<b>Labels:</b>	DRMS

<b>Rationale:</b>	Assess the user engagement to the iFlex assistant DR mechanisms.
<b>Source:</b>	D5.2
<b>Pilot Finland:</b>	Phase two
<b>Pilot Greece:</b>	Phase two
<b>Pilot Slovenia:</b>	Phase two

#### **Description**

The iFlex assistant DRMS should be able to provide to other system components the end-user's data on participation in DR events.

### **Points accumulation according to user participation/actuation**

#### **[IF-76] Capability to store user's performance data and points**

<b>Type:</b>	Functional
<b>Reporter:</b>	<a href="#">Thanasis Papaioannou</a>
<b>Labels::</b>	DRMS

<b>Rationale:</b>	The users may be provided rewards proportionally to their DR performance.
<b>Pilot Finland:</b>	To be determined
<b>Pilot Greece:</b>	To be determined
<b>Pilot Slovenia:</b>	To be determined

#### **Description**

The iFlex assistant DRMS should have the capability to store user performance data on following DR signals (i.e., user DR performance). E.g., participating in a DR event does not necessarily mean that the user fully fulfills the DR objective. Also, meeting the DR objective may be associated to a number of points or other data on user performance.

This requirement is also related to the requirement **FN-AM-18 - Communication of flexibility validation data** (explicit DR), which dictates that the iFlex assistant A&M interface should communicate flexibility validation data to the external DR system.

### **UI for user standing with respect to participation/actuation**

#### **[IF-79] UI for user standing with respect to participation as compared to others**

<b>Type:</b>	Functional
<b>Reporter:</b>	<a href="#">Thanasis Papaioannou</a>
<b>Labels:</b>	UI

<b>Rationale:</b>	Exercise peer pressure to the user with visualization of comparative standing with respect to DR participation as related to other users.
<b>Source:</b>	D5.2
<b>Pilot Finland:</b>	To be considered
<b>Pilot Greece:</b>	Phase two
<b>Pilot Slovenia:</b>	Phase two

#### Description

Visualize relative user participation rate to DR events. E.g., a tree image in a forest, where the size and the greenness of the tree represent high DR participation rate. Negative/aggressive visualization should be precluded.

#### UI for user standing with respect to user performance

##### [IF-80] UI for user standing with respect to DR performance as compared to others

<b>Type:</b>	Functional
<b>Reporter:</b>	<a href="#">Thanasis Papaioannou</a>
<b>Labels:</b>	UI

<b>Rationale:</b>	Exercise peer pressure to the user with visualization of comparative standing with respect to DR performance as related to other users.
<b>Source:</b>	D5.2
<b>Pilot Finland:</b>	Not applicable
<b>Pilot Greece:</b>	Phase two
<b>Pilot Slovenia:</b>	Phase two

#### Description

Visualize relative user performance in DR events. E.g., a tree image in a forest, where the size and the greenness of the tree represent high DR performance. Negative/aggressive visualization should be precluded.

#### Access to user load profiles

##### [IF-78] Access to detailed user load profiles

<b>Type:</b>	Functional
<b>Reporter:</b>	<a href="#">Thanasis Papaioannou</a>
<b>Labels:</b>	A&M

<b>Rationale:</b>	Detailed load profiles of users should be available for incentive mechanism design by the DRMS.
<b>Source:</b>	D5.2
<b>Pilot Finland:</b>	Not applicable
<b>Pilot Greece:</b>	To be considered due to privacy concerns
<b>Pilot Slovenia:</b>	To be considered due to privacy concerns

#### Description

DRMS should be able to access detailed user load profiles, in order to optimally design DR signals and incentives to be provided to users.

#### Access to user preferences

**[IF-77] Access to user preferences on flexibility**

Type:	Functional
Reporter:	<a href="#">Thanasis Papaioannou</a>
Labels:	DRMS

Rationale:	Access to user preferences on flexibility in order to determine optimization constraints for the DR signals.
Source:	D5.2
Pilot Finland:	To be considered
Pilot Greece:	Phase 2
Pilot Slovenia:	Phase 2

**Description**

DR events may be optimized based on user preferences for flexibility provision and the user load profiles. Therefore, access to user preferences should be offered to other components of the system.

**Access to PV generation data / forecast****[IF-81] Access to PV generation data / forecast**

Status:	Open
Project:	<a href="#">iFlex Project</a>

Type:	Functional
Reporter:	<a href="#">Thanasis Papaioannou</a>
Labels:	HEMS

Rationale:	Estimate power generated during the DR event, in order the DRMS to optimize the energy consumption schedule of users to properly meet flexibility objectives.
Source:	D5.2
Pilot Finland:	Not applicable
Pilot Greece:	Not applicable
Pilot Slovenia:	Phase two

**Description**

In the Slovenian pilot, residential users are prosumers that possess power-generation capability via PVs. Being able to access the PV generation historical data or PV power-generation forecast would enable DRMS to optimally design personalized DR signals to be sent to end users during a DR event.

## 8 Conclusions – Future work

This deliverable has overviewed the prior and recent theories for designing effective DR mechanisms for flexibility purposes as well as the relevant experience from practice. In particular, the document presented multiple DR schemes that have been proposed in the relevant scientific literature and has provided the basic mathematical framework for designing an effective theoretically justified DR mechanism. Furthermore, the deliverable has reviewed existing behavioral theories and the behavioral drivers for electricity/energy consumption. To connect theory with practice, the document has outlined the DR campaigns already applied (together with their results) in Greece, Slovenia and Finland, as well as in the EU and elsewhere, and presented the main relevant findings. Based on the respective theory and practice, but also taking into account practical constraints, the deliverable defined the initial incentive and engagement mechanisms to be employed in the Greek pilot site of iFlex, as well as outlined specific ideas for the corresponding mechanisms of the Slovenian and the Finish pilot sites. Finally, the document identified the technical requirements that are imposed to the iFlex architecture and assistant by the proposed incentive schemes for the three pilot sites. These requirements may be properly modified in the future, as a result of a maturity process.

As a final remark, it should be noted that the initial DR incentive mechanisms and schemes will be subject to improvement, according to the insights that the project will gain from the interaction of pilot users with them, but also based on new capabilities that will be enabled due to enhancements in the pilot deployments and/or additional users/user groups.

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## 11 Appendix / Annex

### A simple model for DR targeting under uncertainty.

In this appendix, we develop a simple model for targeting users for DR and offering incentives to them, under uncertainty on whether the desired flexibility will indeed be attained by each of the targeted users. This model pertains to the Greek pilot and particularly to the selection of DR incentives thereto. We assume that there are  $N$  users, indexed  $1 \dots N$ . A subset of them will be targeted for DR. Thus, we define a binary variable  $y_j$  per user, where  $y_j=1$  if user  $j$  is targeted and  $y_j=0$  otherwise.

If user  $j$  is indeed targeted, then he is offered incentives  $r_j$ , in order to meet a demand flexibility (i.e., reduction of consumption in a particular time-zone) equal to  $x_j(r_j)$ . However, we assume that it is not certain that this flexibility is met by user  $j$ . In particular, we model this uncertainty associated with the outcome of DR as a Bernoulli trial, with a success probability  $p_j(r_j)$  that depends on the economic incentives, as well as on the behavioral factors incentivizing users such as peer pressure etc. (see Chapter 4). In case of failure, we take for simplicity that user  $j$  does not attain any flexibility and is not paid the incentives initially offered. The success probability  $p_j(r_j)$  is increasing in the incentives  $r_j$ , with  $p_j(0)=0$  and  $p_j(\infty)=1$ . Also, according to (Minou et al., 2015), for each user the economic incentives should be at least equal to his loss of Net Benefit due to DR, i.e. his loss of utility (due to discomfort) minus his savings in the electricity bill (due to the lower level of consumption). This implies that  $p_j(r_j)=0$  for  $r_j < \text{NBloss of user } j$ . To make our analysis more tractable, we take that  $p_j(r_j)$  is a continuous and differentiable function taking low values for  $r_j < \text{NBloss of user } j$ ; e.g., a sigmoid function.

To simplify our analysis, we take that the demand flexibility requested by user  $j$  does not depend on the offered incentives and thus just equals  $x_j$ . This indeed applies to the case of the Greek pilot, where the demand flexibility stems from shifting the use of his heater for bath water.

We now specify the optimization problem of the flexibility aggregator. We take that the flexibility aggregator has a total budget  $B$  for DR incentives. His objective is to **maximize the expected value of the total flexibility**. That is

$$\begin{aligned} & \text{maximize } \sum_j y_j * x_j * p_j(r_j) \\ & \text{such that } y_1 r_1 + y_2 r_2 + \dots + y_N r_N \leq B \end{aligned}$$

The above maximization is with respect to the binary variables  $y_j$  for  $j=1, \dots, N$  and the incentives  $r_j$  for  $j=1, \dots, N$ . By the definition of the objective function, a user that is not targeted (i.e. if  $y_j=0$ ) does not contribute to the summation under maximization and thus in the optimal solution he is offered no incentives (i.e.  $r_j=0$ ).

If users are symmetric, i.e.  $x_j = x$  and  $p_j(\cdot) = p(\cdot)$ , then the above problem amounts to deriving the optimal number  $n$  of users to be targeted, that is:

$$\text{maximize } x * \{n * p(B/n)\},$$

because, due to symmetry, at the optimal point all targeted users are offered the same incentives.

An alternative optimization problem is to seek for the **minimum total budget for DR incentives** that is necessary for the flexibility aggregator to meet a particular threshold  $X$  for the expected value of the total flexibility. This problem is formulated as follows:

$$\begin{aligned} & \text{minimize } y_1 r_1 + y_2 r_2 + \dots + y_N r_N \\ & \text{such that } \sum_j y_j * x_j * p_j(r_j) \geq X \end{aligned}$$