Intelligent Assistants for Flexibility Management
(Grant Agreement No 957670)

D5.3 iFLEX consumer engagement and incentive mechanisms

Date: 2022-09-30

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: D5.3 iFLEX consumer engagement and incentive mechanisms.docx
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	Christos Krasopoulos (AUEB)	2022-02-15	Initial table of contents
	Christos Krasopoulos, Thanasis Papaioannou, and George D. Stamoulis (AUEB)	2022-07-12	Drafted section 3.1
0.2	Thanasis Papaioannou and George D. Stamoulis (AUEB)	2022-07-12	Drafted section 5.1
0.3	Louise Birch Riley, Trine Sørensen (IN-JET)	2022-07-22	Provided input on social and moral incentives for each pilot
	Nikos Charitos (ICOM)	2022-07-27	Provided input in Section 3.2.3
0.4	Thanasis Papaioannou (AUEB)	2022-07-28	Provided final version of Section 4.1
	Christos Simoglou (OPTIMUS)	2022-08-08	Provided input in Section 3.2.4
0.5	Athanasios Papakonstantinou, Kostas Kalogiannis, Stathis Efthimiou (HERON)	2022-08-12	Provided input in Section 3.2
	Poria Divshali (Enerim)	2022-08-18	Part of section 5.2
0.6	Kos Anton (ELE)	2022-08-18	Section 4.2.1
	Kiljander Jussi (VTT)	2022-08-24	Part of section 5.2
0.7	Kiljander Jussi (VTT)	2022-08-31	Introduction of Section 5
	Andraž Javernik (ECE)	2022-09-07	Section 4.2.2
0.8	Kiljander Jussi (VTT)	2022-09-08	Part of section 5.2
	George D. Stamoulis (AUEB)	2022-09-20	Added Executive Summary and Conclusion
	Thanasis Papaioannou (AUEB)	2922-09-20	Provided final version of Section 5.1
0.9	Christos Krasopoulos (AUEB)	2022-09-20	Ready for internal review
1	Christos Krasopoulos (AUEB)	2022-09-30	Final version submitted to the European Commission

Internal review history:

Reviewed by	Date	Summary of comments
Amir Safdarian	2022-09-23	Provided minor suggestions and comments
Marion Paraschi	2022-09-23	Provided minor suggestions and comments

Index:

1 Executive summary

The purpose of this deliverable is to report on the work carried out by Task 5.3 – *Incentive mechanisms and consumer engagement*, and particularly the work accomplished by this Task, following submission of D5.2. Within this period, the focus was primarily on the development, modelling, and assessment of economic incentive mechanisms for the three iFLEX pilots. A tailored approach was developed for each one of them due to their inherent differences. To this end, appropriate individual models regarding the economic incentive mechanisms and their analysis in this deliverable, together with the respective issues on the practical applicability of these mechanisms and with ideas for their combination with non-economic incentive mechanisms.

In particular, for the Greek pilot, an approach for the optimal management of the flexibility offered by residential users under uncertainty is developed; indeed, such uncertainty in the consumer response to the Demand Response (DR) signals may disrupt the goal of demand flexibility management. Therefore, a probabilistic user model to account for the uncertainty regarding whether a user will indeed achieve the flexibility specified (in conjunction with the incentives offered to this user) is developed and is subsequently introduced in the DR targeting process. Then, a suitable optimization framework to enable flexibility maximization and budget minimization is specified, comprising separate single-objective expressions with the appropriate constraints. Moreover, specific representative problems are defined and solved numerically for a wide range of user parameters, in order to illustrate the applicability and accuracy of the method, and to extract valuable insights. Also, techniques to resolve practical issues and to enable real-world implementation of the proposed scheme in the pilot sites are developed; namely, a mathematical expression to estimate the confidence intervals of the attained flexibility and a learning algorithm for extracting the individual user parameters according to their participation patterns. Finally, practical issues on how to apply this approach in practice, and how to promote user engagement are defined, including the definition of appropriate lottery mechanisms motivated by prospect theory.

For the Slovenian pilot, an optimization framework that provides different forms of economic and non-economic incentives to prosumers with their own renewable resources (as opposed to simply consumers, which is the case with the other two pilots) is specified; this includes rewards, lotteries, peer-pressure, for providing flexibility at specific time slots. Dynamic tariffs per time slot for purchasing and selling electricity are accommodated in this framework as well. The overall problem is formulated as a Stackelberg game, played in turns by the aggregator and the users, and its analytical solution for simple cases of user utility functions is outlined for the case of full information by the aggregator concerning user-utility functions. Moreover, a distributed iterative algorithm is developed for solving the flexibility-management problem in the case where these functions are not known to the aggregator. Numerical results show that this optimization framework is capable to elicit the required flexibility from users at a minimum incentive cost, especially when monetary rewards are combined with peer pressure.

As for the Finnish pilot, flexibility is taken to emerge from the building's heating system, and especially from the thermal mass of the building that can be used to store energy. Flexibility management is based on the assumption that when the heating is turned off the heat energy stored in the building can be utilized to provide flexibility before the indoor temperature drops below the contractually agree lower limit. Therefore, again an appropriate optimization problem is specified; namely, the objective is to maximize flexibility, while several factors are taken into account, such as internal temperature constraints, evolution of this temperature on the basis of external temperature forecast and thermal model of the building, and budget constraints incentives. The case of zero budget is also considered, motivated by the fact that users have agreed to the lower limit of the internal temperature. Numerical results reveal that even when this limit is not violated, the use of monetary incentive to compensate users for their discomfort leads to higher total flexibility. Issues on the practical implementation of the incentives' scheme considered, such as a method for calculating the baseline load, are also discussed.

2 Introduction

The purpose of this deliverable is to report on the work carried out in Task 5.3 – *Incentive mechanisms and consumer engagement,* namely, the work accomplished by this Task, following submission of D5.2. Within this period, the focus of Task 5.3 was primarily on the development, modelling, and assessment of economic incentive mechanisms for the three iFLEX pilots. A different approach was developed for each one of the three pilots due to their inherent differences. Appropriate individual models regarding the economic incentive mechanisms have been developed and analyzed. The respective practical issues have been identified and ideas are provided for the combination of economic and non-economic incentive mechanisms.

The remainder of this deliverable is organized as follows: Chapter 3 contains the model of the incentive mechanisms for the Greek pilot, as well as a discussion on relevant practical issues. Chapter 4 contains the model of the incentive mechanisms for the Slovenian pilot, as well as a discussion on relevant practical issues, while Chapter 5 contains the model of the incentive mechanisms for the Finnish pilot, as well as a discussion on relevant practical issues. Finally, Chapter 6 contains concluding remarks.

3 Incentive mechanisms for the Greek pilot

3.1 Modeling and analysis of economic incentive mechanisms

3.1.1 User Modelling

We consider a provider/aggregator targeting users for DR and offering incentives to them. We define a model regarding the uncertainty on whether the desired flexibility will indeed be attained by each of the targeted users. This model pertains particularly to the selection of DR incentives thereto for motivating a user to indeed refrain from using certain electrical devices. We assume that there are N users, indexed $1, \dots, N$. A subset of them will be targeted (i.e., selected) for DR. Thus, we define a binary variable y_n per user, where $y_n = 1$ if user n is targeted and $y_n = 0$ otherwise.

If user *n* is indeed targeted for a certain DR event concerning a particular time slot, then he is offered incentives r_n, in order to meet a demand flexibility (i.e., reduction of consumption in a particular time-zone) equal to x_n, which is different per customer n and depends on his load consumption profile. We assume that the demand flexibility x_n requested by user n (e.g., turn-off an electric device for a time period) does not depend on the offered incentives, but on his baseline consumption schedule.

In this model, the user is faced with two choices: either to accept the offered incentives r_n and indeed provide the flexibility x_n, or to reject the incentives and maintain his consumption schedule. According to (Minou et al, 2015), if the DR incentives cover user's discomfort (i.e., loss of utility) due to not using certain loads, discounted by the savings in the energy bill, if $r_n \geq NBloss(n)$ (i.e., loss of Net Benefit due to DR), then participation in the DR event is the optimal decision for the user. Therefore, ideally, we can define the minimum acceptable incentives of user *n,* henceforth denoted as $r_{\min(n)}$, and take that the probability $p_n(r_n)$ for user n to participate in the DR event is a step function, rising from 0 to 1 at $r_n = r_{\min(n)}$.

In order to incorporate uncertainty in our analysis, and thus make it more general, we take the outcome of DR as an outcome of a Bernoulli trial, with a success probability $p_n(r_n)$ that depends on the economic incentives. In case of failure in this trial, we take that user n does not participate in DR, and thus he does not attain any flexibility and he is not paid the incentives r_n initially offered to him, and vice versa. This participation-probability function should have the following properties: (1) $p_n(r_n)$ is increasing, continuous and differentiable in the incentives r_n, (2) $p_n(0) = 0$ and $p_n(\infty) = 1$, and (3) $p_n(r_n)$ ascends steeply from low to high values around $r_{\min(n)}$.

Therefore, $p_n(r_n)$ constitutes a smooth approximation of the step function discussed above. Employing such a function rather than the unit-step function also allows for cases where the user can accept (resp. reject) somewhat lower (resp. higher) incentives than $r_{\min(n)}$ since his discomfort by not using the electrical device at the specific time slot can occasionally be slightly lower (resp. higher). A function possessing all of the above properties is the sigmoid function. For a user *n* with minimum acceptable incentives $r_{\min(n)}$, we can take that:

$$p_n(r_n) = \frac{1}{1 + e^{-a_n(r_n - r_{min,n})}} \tag{1}$$

which is a slightly modified version of the sigmoid function, for which $p_j(r_{\min(n)}) = 1/2$ regardless the value of a_n, which however determines how steeply the function rises. In particular, the larger a_n, the steeper the function. Figure 1 illustrates the function shape according to various a_n values.

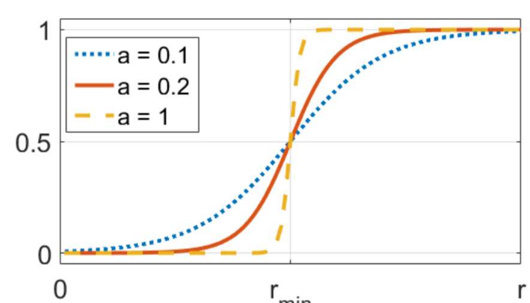


Figure 1: Modified sigmoid function for various values of *a*

3.1.2 Optimization Framework

The optimization problems of the flexibility aggregator can now be specified. We take that the latter has a total budget *B* available for DR incentives. His objective is to maximize the expected total flexibility X_E, without exceeding the total DR incentives budget:

$$\begin{gathered} \max \sum\nolimits_n y_n \cdot x_n \cdot p_n\,(r_n) \\ s.t.\ y_n\ \in \{0,1\}\ and\ \sum\nolimits_n y_n \cdot r_n \leq B \end{gathered} \tag{2}$$

where y_n for $n = 1, \dots, N$ constitute binary decision variables for targeting user *n* and r_n are the incentives offered to user *n*. For obvious reasons, we assume that a user *n* that is not targeted (i.e., if $y_n = 0$) is offered no incentives (i.e., $r_n = 0$). By monotonicity, the budget constraint will be met with equality under the optimal solution.

Extracting the optimal targeting by solving the above problem may prove a conservative and "generous" approach for the provider. Indeed, certain targeted users may ultimately decide not to accept the incentives offered and/or not meet their DR objective and thus rightly not be rewarded by the provider. In such a case, part of the total DR incentives budget would be left unused. To improve on this, we consider alternatively a looser constraint, restricting the expected total DR incentives actually paid. For simplicity, we refer to this metric as the expected total DR incentives, or the expected total reward. The optimization problem becomes:

$$\begin{gathered} max \sum\nolimits_n y_n \cdot x_n \cdot p_n\,(r_n) \\ s.t. \sum\nolimits_n y_n \cdot r_n \cdot p_n(r_n)\ \leq\ B \end{gathered} \tag{3}$$

The optimal solution of the previous problem is clearly a feasible solution of the problem with the less tight constraint. Therefore, a higher X_E can now be attained. However, it is possible that the total reward actually paid occasionally exceeds the threshold *B*.

An alternative (dual) optimization problem is to seek for the minimum expected total DR incentives (reward) that is necessary for the flexibility aggregator to meet a particular threshold X for X_E. This problem is formulated as follows:

$$\begin{gathered} \min \sum\nolimits_n y_n \cdot r_n \cdot p_n(r_n) \\ s.t.\ \sum\nolimits_n y_n \cdot x_n \cdot p_n\,(r_n) \geq X \end{gathered} \tag{4}$$

Similarly, to the above, it is possible that X_E is occasionally lower than the desired level X.

The above optimization problems and the relevant trade-offs can be considered simultaneously by studying a multi-objective scheme. In particular, they can be formulated together in a two-criteria optimization problem, where the first criterion is the maximization of the total expected flexibility obtained and the second criterion is the minimization of the expected total reward B_E (or alternatively of the incentives budget):

$$\begin{cases} \max X_E \\ \min B_E \end{cases} \Rightarrow \begin{cases} \max\ \ \sum_n \left[y_n \cdot\ x_n\ \cdot\ p_n(r_n)\right] \\ \ \min\ \sum_n\left[\, y_n \cdot\ r_n \cdot\ p_n(r_n)\right] \end{cases} \tag{5}$$

This way, we can obtain the optimum values of each criterion separately, and all the non-dominated criteria values in-between. The non-dominated values will correspond to the best compromises between the extreme values of the criteria. The results will provide input for their further post-processing and will shed light on the solutions of the single-objective problems. The Pareto-front shape of the solutions may reveal a saturated relationship between the optimal solutions, indicating that significant improvement in one of the two criteria does not lead to significant loss to the other. With such higher-level information one could decide e.g. to go for a slightly lower total flexibility value if that would bring a significant reduction in the incentives budget. Moreover, the Pareto-front shape could also involve various interchanging regions of linear and saturated nature. This could be an indicator of the regions where uncertainty in the decision space may have a bolder effect on the objectives. These considerations stem mainly from the fact that the criteria are independent and the entity in charge of the decision-making may change his initial perspective on the importance of each objective according to the results.

3.1.3 Analysis

Below, we present special cases of the above problems to be studied first. Our main objectives have:

- to characterize the optimal targeting policies and the impact of certain parameters to the optimal values of the objective function under certain assumptions on the user model;
- to assess the extent of the positive impact of additional information possessed by the provider to the optimal value of the objective function;
- to assess the extent of the positive impact of additional information to the user's well-being.

The latter two objectives, if met, aim to demonstrate the benefit for the user and the provider of employing the iFLEX assistant. Or in general of approaches that attain, convey and/or learn information that is not completely known to the provider.

Below we define certain specific models, with simplifying assumptions, as starting point for our analysis. The relevant optimization problems can be analyzed either in their two-objective version or as a single-objective primal or dual. For brevity reasons, we only present the single-objective primal.

3.1.3.1 Problem 1: Symmetric users

In the first investigation, users are considered symmetric, i.e. $x_n = x,\ r_{\min(n)} = r_{min},\ a_n = a,$ which implies that $p_n(.) = p(.)$. The problem of maximizing X_E for a given incentives budget amounts to deriving the optimal number n^* of users to be targeted and the optimal reward r^* to be offered to each of them, is given by:

$$\begin{aligned} &\max\ \ x \cdot n \cdot p(r) \\ &\text{s.t. } n \cdot r \le B, \qquad n \in \mathbb{N} \end{aligned} \tag{6}$$

because, at the optimal point, due to symmetry, all targeted users should be offered the same incentives r. Clearly, n^* and r^* are constrained by B and depend on the parameters r_{min} and a of the sigmoid participation probability function. Next, we investigate the dependence and the monotonicity properties of n^* and r^* on r_{min} and a.

Figure 2a and Figure 2b depict the relationship of n^* and r^* with a, respectively, for different values of r_{min}. Figure 2a shows that when r_{min} and a both have low values, the max. X_E value is attained by targeting all the users. The number of targeted users decreases, however, as the probability function becomes steeper (a rises) and r_{min} increases. Figure 2b shows that the increase of r_{min} also boosts r^* for each user. As a increases, r^* drops. Figure 2c and figure 2d exhibit how X_E relates to r_{min} and a. Smaller values of r_{min} and greater values of a lead to superior flexibility. The value of r_{min} has a deeper effect on X_E, than a. When a is big, lower incentives are required to achieve the same amount of flexibility.

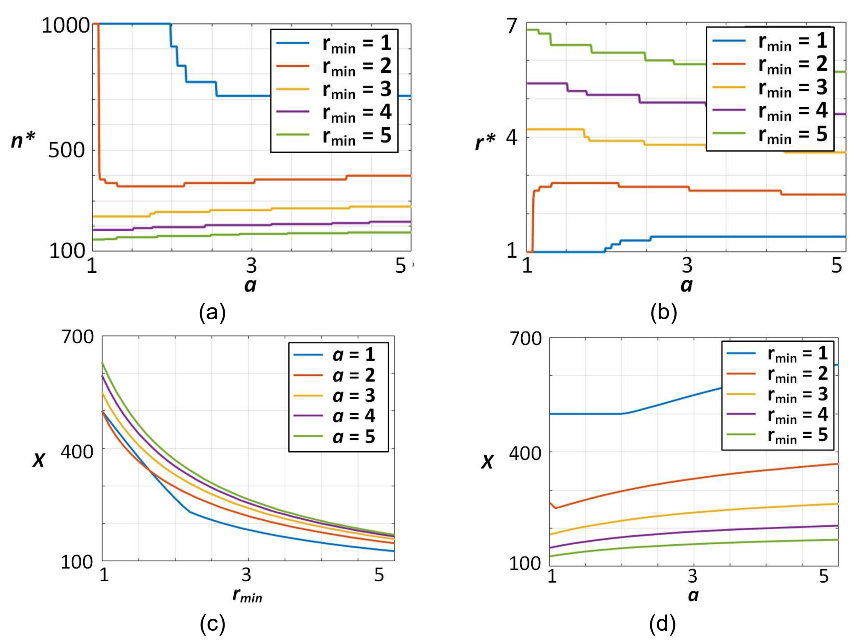


Figure 2: Relationship of (a) n^* and (b) r^* with a for various values of r_{min}. Relationship of X_E with (c) r_{min} for various values of a, and (d) a for various values of r_{min}.

Next, we consider the problem of maximizing X_E with the alternative constraint concerning the expected total reward. The optimization problem is now defined as follows:

$$\begin{gathered} \max \;\; x \cdot n \cdot p(r) \\ \text{s.t. } n \cdot r \cdot p(r) \leq B, n \in \mathbb{N} \end{gathered} \tag{7}$$

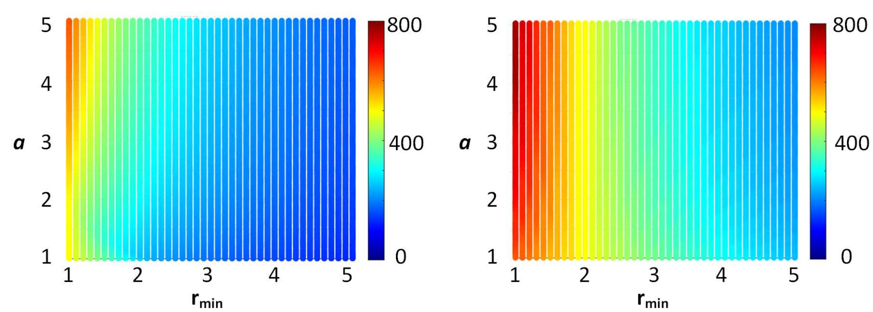
The relation of the maximum flexibility with parameters a and r_{min} is displayed in Figure 3. By employing the *n·r·p(r)* ≤ *B* constraint (Figure 3b) we achieve higher values of total flexibility on a wider span of probability function parameters compared to the flexibility attained under the constraint *n·r* ≤ *B*.

The relation of the ratio r^*/r_{min} with r_{min} and a, is shown in Figure 4 for the two types of constraints regarding B. It can be seen that the $n \cdot r \cdot p(r) \leq B$ constraint involves optimal incentives that are less than the minimum acceptable ones ($r^* < r_{min}$) for the majority of considered parameters. In other words, this constraint leads to the counterintuitive and "risky" policy of offering low incentives to many users. This may also lead to significant budget overshoots in case more users than those expected actually participate in DR. On the other hand, under the $n \cdot r \leq B$ constraint, the optimal incentives are in general higher than the minimum acceptable ones ($r^* > r_{min}$). This constitutes a robust policy since each targeted user now has a high participation probability.

3.1.3.2 Problem 2: Two distinct groups of users

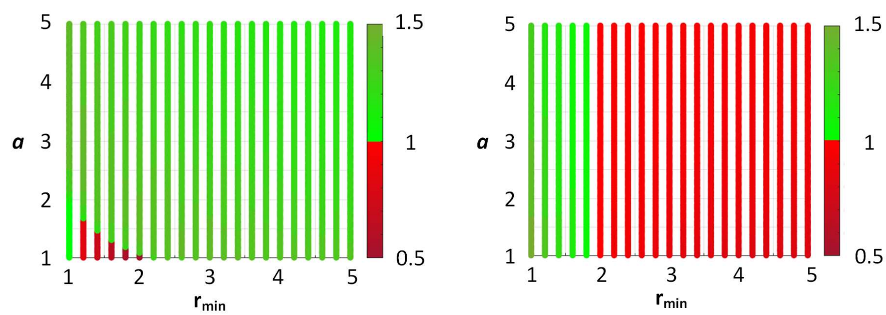
In this problem, users are considered to belong to two types (of identical users each), namely the "small" users with a low flexibility capability x_{low} that also require low incentives r_{low}, and the "big" ones with x_{high} and r_{high} respectively; e.g. single-person households and family-households. For simplicity, we can take that a is common regardless the type. It is interesting to study the properties of the optimal solutions of the optimization problems: Is it preferable to target many small users or a few big users? Or a mixture of users from both types?

Such information can be considered as being provided by the iFLEX assistant, yet only in the case it is fed with detailed information about user parameters etc. To demonstrate the benefit of possession and exchange of such information when employing the iFLEX assistant, we can also consider the case where the provider-side cannot distinguish to which type each user belongs. To make a fair comparison with the case where the group to which each user belongs can be identified, we take that in this case the provider knows the proportion



(a) (b)

Figure 3: (a) X_E with respect to r_{min} and a, under the constraint $n \cdot r \leq B$, (b) X_E with respect to r_{min} and a, under the constraint $n \cdot r \cdot p(r) \leq B$



(a) (b)

Figure 4: (a) r/r_{min} ratio with respect to r_{min} and a, under the constraint $n \cdot r \leq B$, (b) r/r_{min} ratio with respect to r_{min} and a, under the constraint $n \cdot r \cdot p(r) \leq B$.

of users in each type, namely q_{low} and $q_{high} = 1 - q_{low}$, the average flexibility $x_{mean} = x_{low} \cdot q_{low} + x_{high} \cdot (1 - q_{low})$.

Note that for simplicity we take $N_{low} = N \cdot q_{low}$ and thus $N_{hig} = N \cdot (1 - q_{low}) = N - N_{low}$ are both integers. Due to not knowing the exact type per user, the provider solves the optimization problems by considering that all users are identical, i.e., he takes that $x_n = x_{mean}$ and offers each targeted user the average of the optimal pair of incentives, i.e., $r_n = r_{mean} = r_{low} \cdot q_{low} + r_{high} \cdot (1 - q_{low})$, of the case that the user types can be distinguished. The benefit for the provider of being able to distinguish the user types can be quantified by comparing X_E to that of the previous case.

A numerical verification is conducted, regarding the comparison specified above. The parameter space is swept (as presented in Table 1), and the flexibility gains are observed as a percentage of the improvement of X_E when there is lack of knowledge of the user groups, assuming that the respective user groups can indeed be identified. Table 2 shows how the mean X_E gain varies according to the x_{high}/x_{low} ratio and N_{low}, and Table 3 according to the $r_{min,high}/r_{min,low}$ ratio and the parameter a respectively. It can be seen that the $r_{min,high}/r_{min,low}$ ratio and N_{low} have the highest impact on the flexibility gains when the user groups are known. It should be noted that the unused budget is always less than 2%, thus implying that high enough incentives (leading to high participation probability) are offered in general. Overall, the average X_E improvement for the provider is 43% on the complete parameter map exploration, which implies that extraction of the user type by the provider is a very beneficial ability for him.

Table 1: Parameter space boundaries with the respective step

Parameter	Lower bound	Upper bound	Step
x_{low}	1		-
x_{high}	4	6	1
N_{low}	200	800	200
N	1000		-
$r_{min-low}$	1	3	0.5
$r_{min-high}$	3.5	5	0.5
p_{low} / p_{high}	10%	100%	10%
r_{low}	1	5	0.1
r_{high}	3.5	7	0.1

Table 2: Mean flexibility gains for specific parameter values

x_{high}/x_{low} ratio	N_{low}	Mean X_E gain in %
3	200	10
6	200	13
3	400	26
6	400	35
3	600	49
6	600	73
3	800	76
6	800	142

Table 3: Mean flexibility gains for specific parameter values

$r_{min,high}/r_{min,low}$ ratio	a	Mean X_E gain in %
<2	<1	31.8
>2	<1	50.1
<2	>1	32.7
>2	>1	51.1

User benefit

Next, we focus on estimating the benefit of employing the iFLEX assistant for the user, by utilizing certain metrics introduced below. It should be noted that this benefit is apparent because, by employing the iFLEX assistant, the user can participate in DR; for this purpose, the user feeds the iFLEX assistant with certain information. Thus, the interesting matter to investigate is whether the knowledge of detailed user information by the iFLEX assistant is always to the benefit of the user. This issue is investigated next. Again, all the numerical calculations are conducted for the same parameters' space sweep (Table 1). Initially, we are calculating the expected incentives earned per "big" and "small" user in the cases where iFLEX assistant allows the groups to be distinguished and the cases where due to the incomplete user information shared with the iFLEX assistant, the latter does not enable differentiation of how the groups are treated. These expected incentives are calculated by the multiplication of the relevant incentives (r_{high}, r_{low} and r_{flat} – where r_{flat} is the common incentive given in the case of non-differentiation of the groups) with the respective possibility of participation per group of users (p_{high} and p_{low}) and with the ratio of the targeted users of the "big" and "small" user groups to the total number of "big" and "small" users. The latter factor is employed because when user groups cannot be distinguished due to lack of the corresponding information by the iFLEX assistant, all users are considered by the provider as "identical" and thus those targeted are selected at random, with all users being equiprobable. Therefore, the relevant formulas are as follows:

iFLEX assistant with detailed information (user groups distinguished):

$$\begin{aligned} r_{\text{"high" user expected}} &= r_{high} \cdot p_{high} \cdot \frac{n_{high\ targeted}}{n_{high}} \\ r_{\text{"low" user expected}} &= r_{low} \cdot p_{low} \cdot \frac{n_{low\ targeted}}{n_{low}} \end{aligned} \tag{8}$$

iFLEX assistant with less detailed information (user groups <u>not</u> distinguished):

$$\begin{aligned} r_{\text{"high" user expected}} &= r_{flat} \cdot p_{high} \cdot \frac{n_{high\ targeted}}{n_{high}} \\ r_{\text{"low" user expected}} &= r_{flat} \cdot p_{low} \cdot \frac{n_{low\ targeted}}{n_{low}} \end{aligned} \tag{9}$$

The relevant results are shown in the following tables. It can be seen that "big" users would prefer to use the iFLEX assistant with detailed information because it allows them to earn approximately double the rewards (104% gain). On the other hand, the "small" users would prefer that the iFLEX assistant is not fed with detailed information, because they receive 55% less rewards. Indeed, when all users are considered as of the same "average" type, "big" users tend to be offered lower incentives while "small" users tend to be offered higher incentives. Both these effects should have been reasonably expected.

Thus, to make a fair comparison, we consider the following variant of our problem, pertaining to a repeated series of independent DR events (say one event per day). A variation of this model is considered, which is applicable when all users correspond to family households, but: it is possible that on certain days either only one member of the family employs the water heater, and this happens with probability q_{low}, or alternatively all family members employ the water heater (and thus consumer a higher amount of energy), and this happens with probability q_{hig} . It should be noted that we take that the number of small (resp. large) users is N_{low} (resp. N_{high}) in each slot; thus, the choices of type of different users are not independent. When considered in the long run (or with respect to their a priori expected values), all users are characterized by the same value of metrics important to users, e.g. expected total incentives earned, expected net benefit attained etc. The new user metrics can be simply obtained by averaging (over the two types, with weights q_{low} and $q_{high} = 1 - q_{low}$) the corresponding metrics per type of the single-shot version of the problem. Comparison is then made with the metrics of the case where users are not distinguishable due to the lack of detailed user information by the iFLEX assistant. Of course, the metrics of interest to the provider remain the same as in the single-shot version of the problem. It should also be noted that it would seem more natural to take that users are independent and that each of them decides on his type (either small or big) by tossing a coin with probability q_{low} and $q_{high} = 1 - q_{low}$ respectively. However, this simple case of a model is harder to analyze and can be better investigated by means of simulations. The reason is that, under this model, the total number of small/big users varies, and thus the problem with known types should be solved for all their possible values and then averaged with respect to the binomial distribution.

Based on the above, we define the following metric as well (applicable with and without detailed user information by the iFLEX assistant), which corresponds to the expected incentives earned per user averaged over his alternating participations in the two groups:

$$r_{\,user\,expected} \;=\; r_{\text{"high" user expected}} \cdot \left(\frac{n_{high}}{n_{high}+n_{low}}\right) + r_{\text{"low" user expected}} \cdot \left(\frac{n_{low}}{n_{high}+n_{low}}\right) \tag{10}$$

The results pertaining to the simultaneous consideration of both user types according to the above metric are presented in Table 4 and Table 5, which show how the user incentive gains (due to the use of the iFLEX assistant) vary according to the x_{high} / x_{low} ratio and N_{low}, and according to the $r_{min-high}$ / r_{min-lo} ratio and the parameter "a" respectively. It can be seen that the $r_{min-high}$ / r_{min-lo} ratio and N_{low} have the highest impact on the user incentive gains when the user groups are known. Moreover, we can observe cases (of parameter values) where the averaged metric is positive, thus indicating an overall benefit due to the use of the iFLEX assistant with detailed information, as well as cases where this metric is negative, thus indicating an overall loss due to the use of the iFLEX assistant with detailed information. The overall average is a 9% reduction of the expected user rewards due to the use of the iFLEX assistant. This implies that the negative impact to "small" users (who are not over-incentivized anymore) overall prevails to the positive impact of the "big" users. Therefore, to avoid this undesirable effect, the provider can aim for a slightly lower flexibility than the optimal under the iFLEX assistant and offer higher incentives to the targeted users. We expect that under such an approach the provider will still enjoy a considerable benefit by employing the iFLEX assistant while keeping all users adequately incited by sharing this benefit more generously with the users. It should be noted though that since for most of the cases the incentives exceed $r_{min-high}$, targeted users do have a positive net benefit under the use of the iFLEX assistant, both with detailed information, by means of which user groups can be distinguished, and with less detailed information, by means of which user groups cannot be distinguished.

3.1.3.3 Problem 3: Flexibility reselling in the market

Next, we investigate the case where the flexibility attained is resold in the market; then, the provider earns some revenue and achieves an economic profit P. This profit equals the revenue from this resale minus the expected total incentives paid. The latter term (according to the preceding analysis) is almost equal to the incentives budget if this is given or is obtained as a result of solving the dual optimization problem of optimal targeting. In the case of dual optimization, both the revenue and the incentives budget depend on the targeted amount X_E of the expected total flexibility. Therefore, if the provider has the opportunity to select this value

Table 4: User incentive gains for various parameter values "freeze"

$\mathrm{x_{high}} / \mathrm{x_{low}}$ ratio	N_{low}	Incentive gain in % for "big" users	Incentive gain in % for "small" users	Incentive gain in % for the users combined
3	200	18.6	-72.8	-2.7
6	200	18.3	-82.6	-4.9
3	400	45.4	-69.6	-6.4
6	400	54.9	-81.8	-6.7
3	600	113.4	-75.3	-10.5
6	600	130.4	-86.3	-10.5
3	800	370.0	-77.8	-13.3
6	800	388.4	-88.0	-12.8

Table 5: User incentive gains for various parameter values "freeze"

$\mathrm{r_{min,high}}/\mathrm{r_{min,low}}$ ratio	*a*	Incentive gain in % for "big" users	Incentive gain in % for "small" users	Incentive gain in % for the users combined
<2	<1	133.0	-66.9	-5.2
>2	<1	85.4	-52.5	-14.3
<2	>1	133.5	-63.6	-4.6
>2	>1	89.5	-46.4	-11.3

within a certain range, he should determine (by means of an "outer" optimization loop) the amount X_E^* of flexibility that leads to optimal expected profits. If pricing of flexibility is linear, i.e., each flexibility unit is resold at a price q, then the relevant optimization problem is as follows:

$$\max q \sum_n [y_n \cdot x_n \cdot p_n(r_n)] - \sum_n [y_n \cdot r_n \cdot p_n(r_n)] \quad \text{s.t.} \sum_n y_n \cdot r_n \leq B \tag{11}$$

Initially, the effect of the total X_E target and the selected *B* is studied with respect to P. To investigate the problem numerically, we take the following parameter and variable value ranges according to Table 6. Similarly to the previous investigations, we sweep the parameter space and optimize for P in every set of parameter values. At first, the expected total flexibility X_E is considered as the optimization objective. This consideration allows for a useful investigation of the relationships among X_E, B and P. The results are presented in the following figures.

The first set of results (depicted in Figure 5) show how P relates to B for various values of r_{min}. It can be seen that the profit curve comprises three segments:

1) A linear segment, for small values of B. In this region, P increases almost linearly with the increase in the number of targeted users. Every single new user entering the DR event is a new source of profit and the profit equals practically the product of the profit from each user with the number of the participants.
2) A saturated segment, where the profit margin begins to shrink until it reaches its peak value. In this area, the maximum number of users is targeted, and incentives are increased across all users to increase their participation probability.
3) A decreasing segment, where regardless of the increase in the incentives, the probability of the users participating is already very close to 1, and thus any further increase in the budget does not provide any gain. It can also be seen in Figure 5a that the r_{min} value strongly affects the slope of the linear part and the maximum profit, but not significantly the profit in the highly saturated area (decreasing part).

A useful insight from Figure 5a is also the dependency of the profit to the minimum acceptable incentives. The r_{min} value strongly affects the slope of the linear part and the maximum profit but not significantly the profit in the highly saturated area (decreasing part).

Figure 5b shows how P relates to X_E for various values of r_{min}. The optimal profit is maximized for a flexibility value that is smaller than the maximum that can be attained. The same segments as in Figure 5a can also be identified in this case; namely, a linear, a saturated and a decreasing part, which apply now for the same reasons as before. It should be noted that the optimal profit, as seen in Figure 5b, is maximized for a flexibility value that is smaller than the maximum that can be attained. Indeed, the max. X_E is accompanied by the saturation of the participation probability p, which is achieved by offering high incentives, thus leading to low profits. The value of r_{min} has a significant impact on the value of P.

In Figure 6, we turn our attention to the Net Benefit (N.B.) of the user and examine how this relates to P and X_E for various values of r_{min}. In Figure 6a, three regions can be distinguished:

1) A constant N.B. region, where its value almost coincides with the x-axis and remains constant, while P increases. The targeted number of users here is less than maximum. The N.B. is the same for all the selected users and does not depend on their number.

Table 6: Parameter/variable space boundaries with the respective step

		Lower bound	Upper bound	Step
Parameter	***q***	10		-
	x	1		-
	a	1		-
	B	100	10,000	100
	r_{min}	1	5	0.1
Variable	***n***	1	1000	1
	r	1	10	0.01

2) A region of mutual profit (for the DR aggregator and the user), where the increase in P also leads to an increase in user N.B. This is the case where incentives improve across all users, after they have been all targeted. The provider gains in P due to the higher probability of DR participation, and users benefit as well.

3) The almost-maximum flexibility region, where P decreases, N.B. continues to grow indefinitely and X_E is asymptotically maximized.

It is interesting to notice that the maximum profit for the provider can be accomplished with a significant benefit for the user, so that both sides are satisfied. It is also important that the provider has the option to decrease his profit in order to make the users happier while still providing the electrical system with a rich level of flexibility.

The current investigation does not quantify the benefit of the electrical transmission and the distribution systems. In general terms, increasing the flexibility from the demand side can only have a positive influence to both of these systems, since it will enable the interruption of non-RES (Renewable Energy Sources) production units for longer time periods and enable the inclusion of more RES units in the grid. At the same time, the existing RES units could operate at their maximum capacities if it is known that the demand is flexible and the power will be consumed, thus achieving a higher penetration in the system. This translates to monetary savings that could be compensated in the future by the market operator and provide another source of revenue for the provider (DR aggregator), so that he may choose to further incentivize the users. In other words, the loss of profit of the provider towards maximizing the demand response success could be compensated in a different manner from the energy market mechanisms.

Next, we investigate the effect of the reselling price q per flexibility unit to the required B and P. The corresponding results are depicted in Figure 6b. We take that the value of q varies from number 0.5 to number 10 with a step of 0.5, while r_{min} is fixed and equal to 3. We can observe that the profit of the provider is increasing in the reselling price q. This is expected since $P = q \cdot X_E - B$, for a given B. To achieve the maximum P for a specific value of q, the budget B should be adjusted accordingly. In general terms, as the resale price increases, the budget should also increase, in order to attain a higher profit.

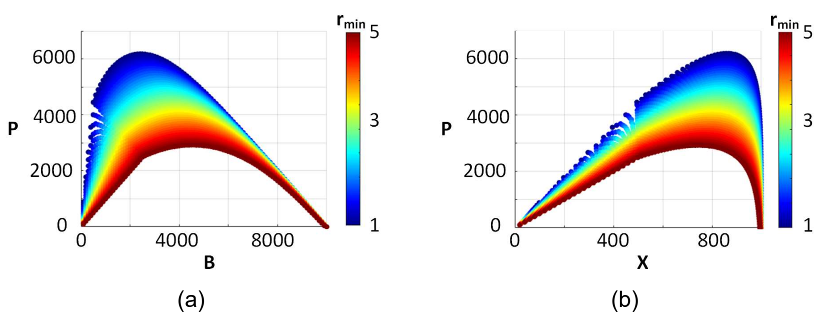


Figure 5: Profit of the provider P with respect to (a) B (b) X_E, for various values of the minimum acceptable incentives r_{min} of the users.

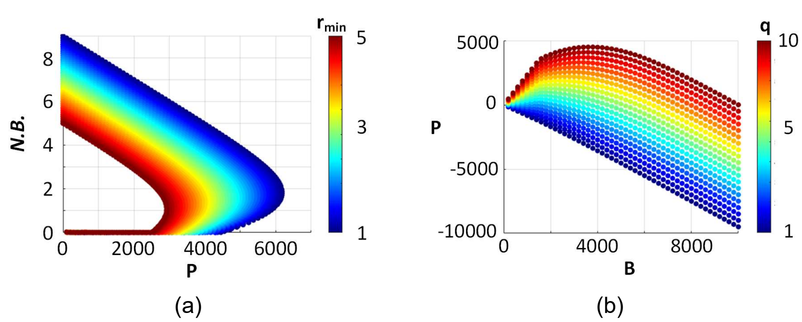
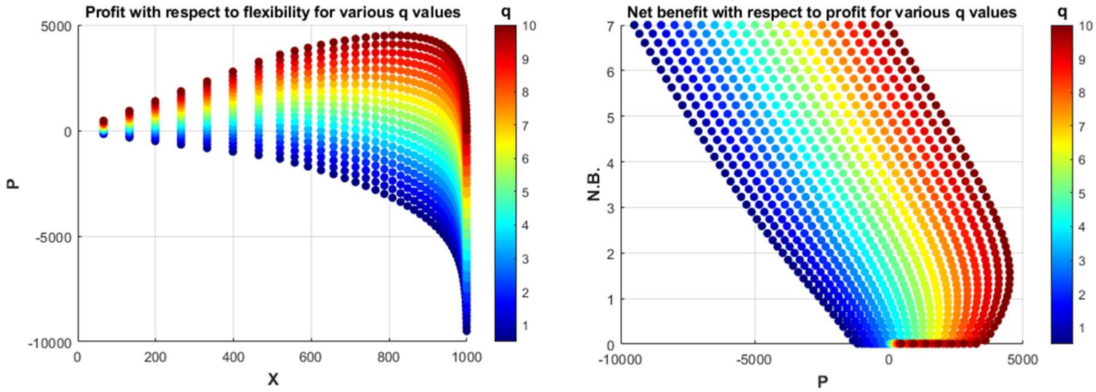


Figure 6: (a) User Net Benefit (N.B.) plotted against the profit of the provider P for various values of the minimum acceptable incentives rmin of the users, (b) Sensitivity analysis of the profit of the provider P with respect to B for various values of the resale price q.



(a) (b)

Figure 7: Sensitivity analysis of (a) the profit of the provider P with respect to the expected total flexibility X and (b) the user net benefit (N.B.) with respect to the profit P, for various values of the resale price q.

Moreover, there is a region for certain ranges of *B* and *q* where the profit is negative, i.e., it corresponds to monetary loss for the provider. In such a case, the DR program is not beneficial for the provider and cannot even be sustained.

Interestingly, we can observe in Figure 8a that the profit depends both on the flexibility target *X* and the resale price *q*. If we draw a horizontal line from a certain value of P>0, we notice that this profit *P* can be attained for certain top values of *q*, and as *X* increases, this profit *P* is achievable until the value of *q* reaches a minimum, and then it can be achieved again for the same higher values of *q*. That is, for each specific resale price *q* within a certain range, the same profit *P* is attained for two different values of *X*. This applies due to the asymptotic behavior of the participation probability *p* towards the value of 1: when all users have been targeted, it becomes more difficult to engage their full potential of flexibility because the incentives have to be increased up to the point where the probability p becomes nearly equal to 1. The next figure (Figure 8b) shows that the user can have the same net benefit for different values of the profit *P* and the resale probability *q*. If the energy market resale policy is negotiable (rather than being predefined), then the aforementioned observation illustrates the potential for the provider to select his resale policy and profit without affecting the user benefit. Also, in such a case, if a provider targets a specific profit, then he can also increase the user net benefit by achieving an increased the resale price. Finally, if the provider decides to resort to higher *q* values, there will be exactly two different values of *q* for which the same profit *P* is attained: one with a low and one with a high user net benefit value; this can be seen by drawing a vertical line from the point of the horizontal axis corresponding to this value *P* of the profit. The higher value of N.B. corresponds to a smaller value of flexibility than the lower one.

Directions for extensions:

- The parameters x_n, a_n and $r_{min(n)}$ of individual users (or collectively of user types) may depend on contexts, such as month, day of the week, vacation periods etc. In such cases, the relevant optimization problems should be considered separately, one per context.
- We have assumed complete information possessed by the provider, particularly when employing the iFLEX assistant. In fact, it is important to couple the aforementioned optimization problems with approaches for learning of the information employed (mainly of a_n and $r_{min(n)}$), on the basis of each user's feedback, namely acceptance and rejection decisions regarding DR incentives offered.
- We have only formulated single-shot problems, involving one DR event each, or multi-slot problems with independent DR events. Thus, multi-slot problems with DR events that are dependent should be considered. In particular, the main "source" of such dependence is to allow for targeted users to shift their bath to the next slot, rather than fully postpone it. Stochastic optimization techniques may prove useful in this case.
- We have only considered economic incentives. As explained in detail as well, behavioral traits can also be very influential in user's incentivization, and thus should also be incorporated in our models. Some preliminary ideas towards this direction have as follows: If a particular user is known to be altruistic or environmentally conscious, then his value of $r_{min(n)}$ should be discounted by a factor lower than 1. Also, if users are influenced and incentivized positively by the participation of a larger number of other users in DR (i.e., peer pressure), then the number of targeted users $\sum_n y_n$ (or a function thereof) should be included in the formulae in such a way that, if it is large, then lower values of incentives are sufficient.

3.1.3.4 Summary and lessons learned

A simple DR model was proposed for the case of the iFLEX Greek pilot, taking also into account the provision of incentives from the provider to the user. In this case, the possibility of user participation is modeled by a formula that depends on two parameters. The first reflects the responsiveness of the user to the incentives provided, and the second constitutes the minimum incentives that must be provided to the user so that he will be more likely to participate than to avoid taking part in DR. On the provider side, the model considers his ability to define flexibility values to be requested by each user and the relevant incentives. Three investigations were carried out on the problem based on different assumptions.

In the first investigation users are taken as symmetric. In other words, they are considered to have the same probability of taking part in DR because they have the same parameter values and are offered the same incentives. Optimization takes place for the maximization of the total flexibility to be obtained with regards to a parameter space sweep (keeping a constant budget) and useful insights are collected:

- When the users are characterized by low responsiveness and low minimum incentives, the optimal number of users to be selected for targeting is large. When each of these two parameters increases, the respective number decreases.
- It is for the benefit of the provider to select users that are more responsive, because the offered DR incentives will be smaller. Also, users that have a low minimum incentives value require minimal incentives.
- The number of users to be selected, the incentives to be provided and the total flexibility to be obtained depend considerably more on the users' minimum incentives, than on their responsiveness.
- The total flexibility earned will be maximized when selecting more responsive users that are also characterized by low minimum incentives.
- When employing a budget constraint that includes the probability of user participation in DR, higher values of total flexibility are achieved on a wider span of probability function parameters, compared to a formulation comprising the "strict" budget constraint that applies even when all targeted users do participate in DR.
- However, the inclusion of the participation probability enables the discovery of optimal incentives that are less than the minimum acceptable ones for most of the previous cases. In other words, this constraint leads to the counterintuitive and "risky" policy to offering low incentives to many users. This may also lead to significant budget overshoots in case more users than those expected actually participate in DR.
- The formulation with the aforementioned "strict" budget constraint leads to optimal incentives that are higher than the minimum acceptable ones for the majority of the cases of parameters considered, and thus to a "robust" incentive's policy, which is considered as more realistic, even though it falls behind on the forecasted total flexibility

Therefore, **the main lesson from this investigation is that the "strict" constraint on the total DR incentives budget** (rather than that on the expected total incentives to be paid) should be considered in practical cases. Moreover, it is for the benefit of the provider to locate and engage the highly responsive users, since the DR program shall not only be cheaper but will also be more successful in terms of flexibility.

In the second investigation, the population of consumers consists of users with low capability of flexibility provision and low minimum incentives (referred to as «low» users) and users with high respective values (referred to as «high» users). The distinction can be made feasible thanks to the iFLEX assistant. The advantage of this knowledge is investigated here, compared to the previous simple case. In other words, it is explored whether possession and exchange of such information through the iFLEX assistant provides benefits for the provider and/or the users.

- Results show that the groups' distinction provides an average flexibility improvement for the provider of 43% when sweeping the complete parameter map. The gains range between 10% and 140%.
- When the ratio of the minimum incentives of the «high» users to those of the «low» users is high, knowledge of user groups becomes significantly more advantageous for the provider. This ratio also has the highest impact on the user incentive gains.
- It is also to the greater advantage of the provider when the group of «high» users is considerably smaller than group of «low» users.
- Group distinguishing is not always to the user benefit. «High» users would prefer the iFLEX assistant to be in position to classify them, since they earn on average double the rewards. On the other hand, «low» users would receive approximately half of the rewards compared to the case where all users are considered as belonging to the same "average" type.

- In a horizontal averaging over the entire space of parameters, the user rewards are characterized by a reduction of 9%. However, there is a broad range of parameter values where this average is positive.

Therefore, **the main lesson from this investigation is that, in order to avoid this undesirable effect, the provider should aim for a slightly lower flexibility than the optimal under the iFLEX assistant and offer higher incentives to the targeted users**. We expect that under such an approach the provider will still enjoy a considerable benefit by employing the iFLEX assistant **while keeping all users adequately incited by sharing this benefit more generously with them.** This is also in line with the increased priority and preference that users appear to have recently for economic incentives, in light of the increased energy bills. Moreover, we can see that adequate knowledge of the user groups, transfers part of the profit from the users (particularly from those whose incentives were considerably overestimated due to lack of information) to the provider without necessarily affecting the flexibility target. Although not modeled specifically, we can also imagine a case where the aggregator represents a cooperative of users. In this case, the optimal benefit for the aggregator will be shared among the users even more favorably for them.

In the third investigation, we assume that the flexibility attained from a population of uniform users is resold in the market. The provider then achieves a profit by earning revenue from the flexibility. The most important findings are the following:

- The profit of the provider increases in an almost linear pattern as the number of targeted users rises until the point where everyone is targeted. After this point, to further increase the profit, the incentives must be increased for all the users. This gradually creates a saturation, and the profit receives a peak value. After this, the profit decreases again.
- The user's net benefit remains constant as the number of targeted users increases. When everyone is targeted and the provider further increases the incentives, the user's net benefit increases, while the provider profit rises as well. After the profit peak, the net benefit continues to increase, and the total flexibility saturates in this region.
- As a result, the maximum provider profit can be accomplished with a significant benefit for the user, so that both sides are satisfied. In this case, the electrical system also benefits because, in general terms, the greater the flexibility, the bigger the RES penetration.
- When the minimum incentives that the users are willing to accept have a small value, the profit for the provider rises faster as more users are targeted and vice versa. The peak value of the profit is also affected by the minimum incentives.
- The profit is maximized for a flexibility value that is smaller than the maximum that can be attained and depends both on the flexibility target and the flexibility unit resale price.
- Regarding the relationship between the provider profit and the unit resale price, the former is increasing in the latter.
- The budget may be adjusted to maximize the profit for a specific unit resale price. In other words, as the resale price increases, so must the budget to increase the profit. However, for certain budget and resale price values the profit turns negative.
- Interestingly, the provider can select his resale policy and profit without affecting the user benefit.

Therefore, one of the main lessons learned from this investigation is that with careful selection of parameters, i.e. incentives budget and flexibility unit resale price (if negotiable) can lead to "all-win" situations, i.e. beneficial for all players involved in the corresponding value chain. Moreover, reselling (by the provider) of the flexibility in the market gives rise to a different value chain that offers new opportunities and indirectly associates the grid benefit to stronger user and provider incentives.

According to the previous summary, the following **guidelines** for the estimation of DR incentives for the Greek pilot can be deduced:

- The incentives provided to users should be at least equal to the minimum each of the user groups requires.
- On a next step, the provider should employ clustering techniques to split the user base in groups of similar characteristics. This will magnify his revenue and subsequently profit without increasing his budget. The more diverse the user groups are, the stronger the advantage of discriminating them.
- Further incentivization of the users after engaging all of them may provide more flexibility, but the trade-off with the budget should be considered carefully in this case.
- If the flexibility is resold in the market, then the provider must seek for his profit maximization; this will also provide the maximum profit to the users.
- The price of the flexibility unit should ideally be as high as possible regardless any other parameters.

- In all cases, optimization and sensitivity analysis are suggested to find the optimal trade-offs, also considering the uncertainty of the user parameters if possible.

The above guidelines apply to the estimation of **economic DR incentives**. However, **these can be complemented by non-monetary incentives**, in a way that works favorably for both the users and the provider. To this end, the following guidelines apply:

- The provider should try to engage users that can be compensated (at least partly) by means of non-monetary incentives. He should determine the age groups, social status e.t.c. of such users and begin DR targeting from them.

As a rule of thumb, targeting of as many users of the previous type as possible is advised.

3.1.4 Practical Issues

3.1.4.1 Confidence intervals

An important aspect of the optimization problem is defining the confidence that the targeted X_E will indeed be obtained. In the case of identical users, the total number of users participating successfully in DR follows the binomial distribution. Calculation of bounds in the possibility that a random binomial variable deviates by a percentage from its mean value can be calculated by the probability mass functions of the binomial distribution, which is an accurate, although computationally intensive way.

In our study of the incentives for the Greek pilot of iFLEX, the stochastic nature of the human decision is modelled means of the Bernoulli trial approach. Therefore, in case of identical users, the total number of users participating successfully in DR follows the binomial distribution. Calculation of bounds in the possibility that a random binomial variable deviates by a percentage δ from its mean value can be accomplished by means of the Chernoff bound, from either one of the equations below:

$$P(X \leq (1-\delta)\mu) \leq \left(\frac{e^{-\delta}}{(1-\delta)^{1-\delta}}\right)^{\mu} \tag{12}$$

$$P(X \leq (1-\delta)\mu) \leq \left(\frac{e^{-\delta}}{e^{-\delta+\frac{\delta^2}{2}}}\right)^{\mu} = e^{\left(\frac{-\delta^2\mu}{2}\right)} \tag{13}$$

where μ is the expected value of the binomial random variable (in our case the number of targeted users multiplied by the common probability of successful participation), and δ is the deviation bound from the expected value. It should be noted that the equation (12) provides a tighter bound, while equation (13) a computationally simpler one:

$$\left(\frac{e^{-\delta}}{(1-\delta)^{1-\delta}}\right)^{\mu} \leq e^{\left(\frac{-\delta^2\mu}{2}\right)} \tag{14}$$

Assuming an example where $\mu = 500$ and a deviation $\delta = 10\%$, the result of (12) shall be 7.5% and the result of (13) 8.2%. Another means of calculating the respective probability is by utilizing the normal approximation of the binomial distribution. In this above example, this shall result in a probability of 0.087%. Comparison of the two methods shows that the Chernoff bound is rather conservative. On the other hand, the normal approximation does not necessarily offer a bound to the deviation probability in consideration. Therefore, in the calculations to follow, we resort to direct computation of the probability mass functions of the binomial distribution, which is accurate, although computationally intensive.

We shall run an optimization problem to track the optimal number n of targeted users and the incentives r to be offered to each one of them under the criterion of minimizing the total incentives offered. At the same time, the respective bounds from the binomial distribution will be calculated. We assume a homogeneous population where all users are characterized by the same a and r_{min} parameters. We take that the aggregator budget is not constrained and that the minimum total flexibility to be attained is 500. The values and/or limits of the respective problem parameters and variables are shown in Table 7.

In this optimization investigation the possibilities of X_E deviation from two types of boundaries is also calculated and presented. It can be seen in Figure 8a that the possibility of the actual value being less than the nominal is significant and is between 44% and 49%. As we begin lowering the minimum bounds that we are willing to

Table 7: Parameter/variable space boundaries with the respective step

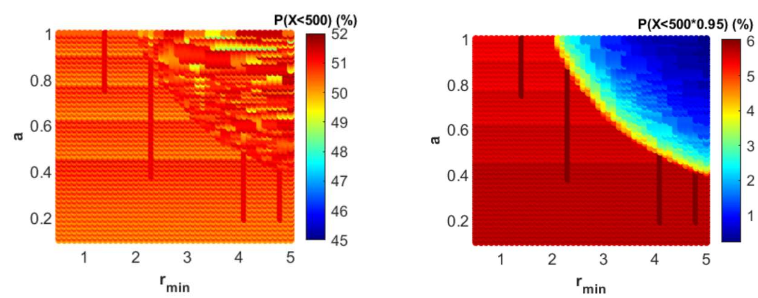
	Lower bound	Upper bound	Step
x	1		-
X	500	-	-
B	-	-	-
N	1	1000	1
r_{min}	0.5	5	0.1
a	0.01	1	0.01
n	1	1000	1
r	1	10	0.1

accept then the possibility steeply drops, e.g., if we are willing to accept a $0.95 \cdot 500 = 475$ value then the likelihood of a lower value than that is below 6%.

Now, let's suppose that we desire a low probability of the flexibility dropping below the nominal value, e.g. 5%. We can run the optimization again for a greater flexibility target that is selected, for example as $500/0.95 = 526.3$. We could see how the new incentives' offers and the rest of the quantities differ with respect to the previous optimization. We can see in Figure 9a that B is not significantly affected, except for the cases of highly unresponsive users (low a). Most importantly, we see in Figure 9b that the likelihood of X_E dropping below 500 is always lower than 5%. If flexibility to be obtained is found to be unacceptable then the target could be adjusted upwards in order to achieve the desirable confidence, according to, e.g., the penalty.

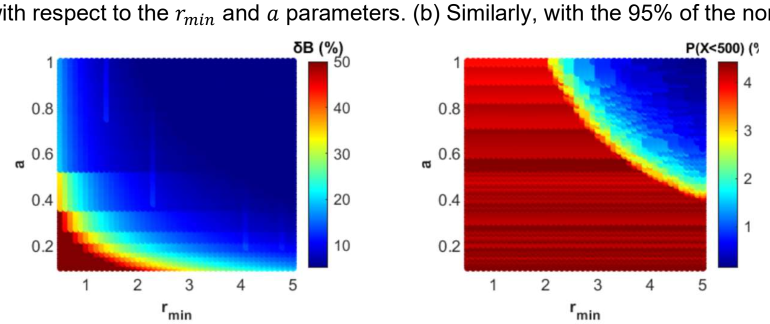
A general conclusion of this investigation is that if there is a hard constraint on the actual flexibility to be obtained, in case e.g. there is a flexibility boundary violation penalty imposed from the market, then the probability of deviation should be calculated during optimization. If this value is found to be unacceptable then the simplest solution would be to adjust the target upwards in order to achieve the desirable confidence, according to e.g. the penalty. Alternatively, the acceptable probability of deviation can be part of the optimization problem as well, in order to keep only the solutions that are safe. A formulation for this would be:

$$\begin{cases} \min y_1 \cdot r_1 \cdot p_1(r_1) + y_2 \cdot r_2 \cdot p_2(r_2) + \cdots + y_N \cdot r_N \cdot p_N(r_N) \\ such\ that\ \sum_n y_n \cdot x_n \cdot p_n(r_n) \geq X\ and\ P\left(\sum_n y_n \cdot x_n < X\right) < \delta \end{cases} \quad (15)$$



(a) (b)

Figure 8: (a) Possibility that the actual flexibility value obtained is below its nominal value according to the binomial distribution with respect to the r_{min} and a parameters. (b) Similarly, with the 95% of the nominal value.



(a) (b)

Figure 9: Differentiation of various quantities when optimizing with a X_E target of 500/0.95=526.3 instead of 500. (a) Difference of total budget expenditure in % and (b) probability that $X_E < 500$ with respect to r_{min} and a parameters.

where δ is the desired threshold of the probability that the total flexibility actually attained has value lower than its target. In fact, for low values of δ, the constraint on the probability will be the binding one, thus rendering that on the expected total flexibility redundant. Also, in certain cases, it may be meaningful that the direction of the inequalities in the constraints is the opposite, e.g., if there is a hard constraint on the maximum flexibility due to e.g. network constraints because of congestion.

3.1.4.2 Learning of DR parameters

In this section, we introduce and evaluate an algorithm to identify the user DR parameters of each user without previous knowledge whatsoever. With those parameters captured, the p of each user will be fully known, the real user will thus be modelled, and the optimization algorithms of the provider will be in position to provide the optimal targeting.

The basic concept of the algorithm can be outlined as follows. Initially, the provider begins offering DR incentives randomly. This approach can be employed for all users at the beginning of the DR program, and also upon entry of every new customer in the program. While incentives are offered, the participation or not of the user in each DR session is observed and recorded (as a binary variable), along with the value of the respective incentives. For each incentives' value, the ratio of the number of times that the user participated to the number of times the user was targeted, constitutes the participation rate. The participation rates for each value of incentives make up the user participation rate pattern. If the user parameters were known, a similar pattern could be calculated with the probability function and this would be equal to the user participation rate pattern, at least theoretically for infinite DR attempts. We will show, however, that only a relatively small number of attempts suffices for the two patterns to be almost equal. Continuing with the description of the algorithm, in every DR attempt, the user participation rate pattern is calculated. The respective patterns for all the possible a and r_{min} values have been also calculated and the two are continuously compared. The pair of parameter values that constitutes the best match for the two is the solution.

The respective mathematical representation follows. To simplify the formulation, the expressions below refer to a single user n. The participation rate pattern s for the value r of DR incentives can be defined as:

$$s_r = \frac{q_{r,k(r)}}{k(r)} \tag{16}$$

where $q_{r,k(r)}$ is the number of times the user participated in DR and $k(r)$ the number of times the user was targeted with DR incentives equal to r. Since $q_{r,k(r)} \leq k(r)$ there follows $0 \leq s_r \leq 1$. This rate is different for each incentives' value r. This pattern is updated after each DR session. The respective pattern, when calculated by the user model is provided by (1). Thus, the goal of the algorithm is then to specify the optimal values for parameters a and r_{min} that minimize the Root Mean Square Error (RMSE) between s and p:

$$\min(RMSE) = min\left(\sqrt{\sum_{r=r_{min}}^{r_{max}} \left(s_r - p(r)\right)^2}\right) \tag{17}$$

To illustrate the method attractiveness, we employ the algorithm to identify 3 random users, A, B and C with a 0.1, 0.5 and 1 and r_{min} 50, 80, 20 respectively. Parameter values have been selected in a such way that different shapes of the probability function are acquired. Figure 10 illustrates the shapes of the probability function for the three random users A, B and C.

Regarding the incentives, we have assumed two schemes:

1) random offers (open loop procedure)
2) predictive method (closed loop procedure)

In the open loop scheme the incentives are provided randomly. In the closed loop scheme, the current estimation of r_{min} and a values in each iteration are employed to predict more relevant incentive values for the next DR event. More specifically, for the current r_{min} and a values, the incentive values corresponding to probabilities 10% and 90% are calculated. The next offered incentive will be a random number, uniformly chosen between these two values.

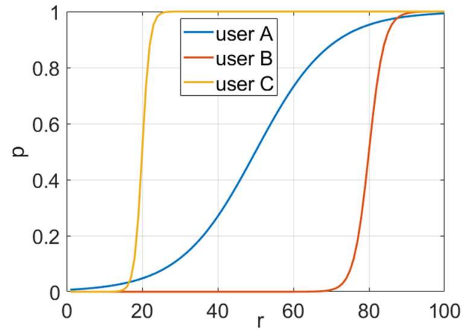


Figure 10: Probability function shape illustration for the random users A, B and C

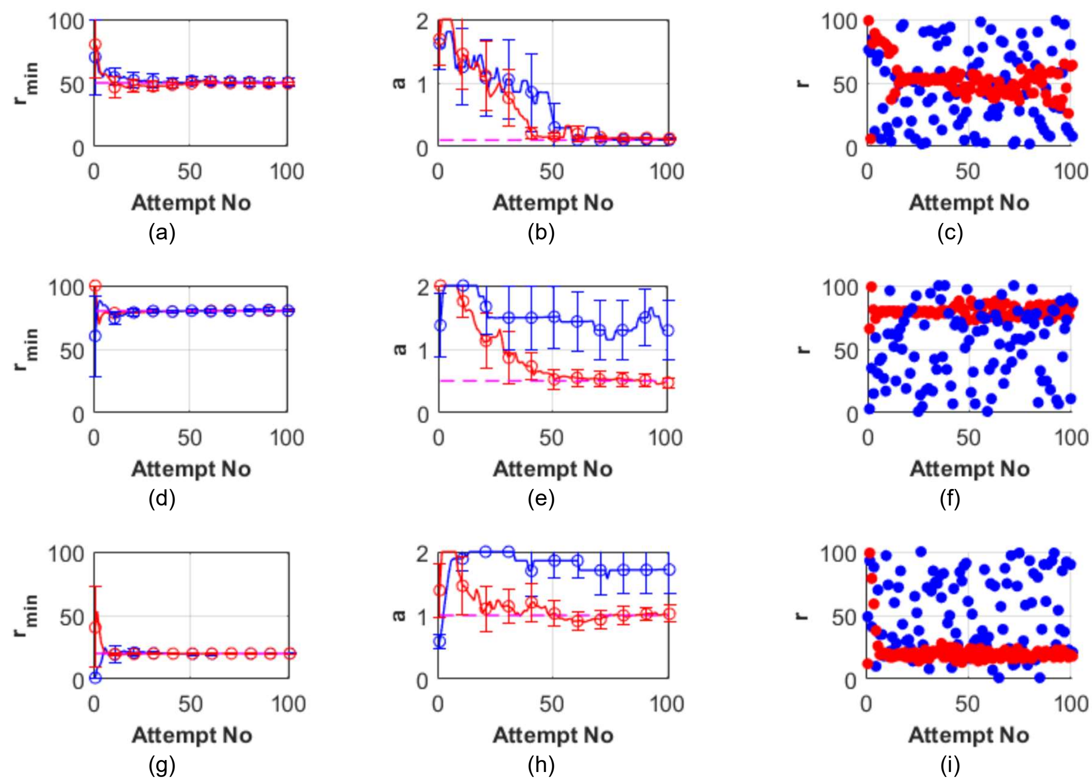


Figure 11: Parameter identification efficiency test for the 3 random users (user A: a, b, c – user B: d, e, f – user C: g, h, i). The first column (a, d, g) illustrates the r_{min} convergence, the second column (b, e, h) the *a* convergence and the third column (c, f, i) shows the values of the *r* offerings. Blue color corresponds to the random method and red color to the predictive one.

The procedure is repeated 10 times, the results are averaged and illustrated in Figure 11. Blue colour corresponds to random offering and red colour to the predictive method. The following conclusions can be extracted:

1) It can be seen that only a relatively small number of attempts (i.e., between 5-20 and sometimes even smaller) suffice to approach the r_{min} parameter with remarkable accuracy.
2) Prediction of responsiveness a is more challenging. However, precise identification of the value of this parameter is of considerably lower importance than the identification of r_{min}.
3) The random offers' method is efficient towards capturing r_{min}, but is rather poor regarding α.
4) The predictive method improves even further the speed of convergence of r_{min} and enhances drastically the speed of identifying parameter ***a***.

It should be recalled that the only feedback available from DR sessions is whether the user participated or not in each event. This is a poor case of feedback and this renders parameter identification a difficult task. Considering this adversity in conjunction with the above satisfactory test results, we conclude that the learning algorithm can be considered as rather efficient; this applies particularly to the closed-loop method.

The convergence speed of the predictive method is increased, especially in the case of greater a values, because the algorithm avoids offering incentive values that lie in the saturated areas of the function, where no useful information is extracted for the shape of the function. The closed loop method offers incentives only within this region, thus accelerating the identification of the probability function shape.

3.1.5 Conclusion

We defined an optimization framework that considers uncertainty in the user responsiveness in DR for flexibility management subject to budget constraints for incentives. We numerically analyzed the influential factors for flexibility management under such uncertainty and we proposed a practical, yet effective, learning algorithm to identify the minimum acceptable incentives and the DR responsiveness of users in real deployments. Our main findings are as follows: The aggregator should locate and engage the highly responsive users, since the DR program will be more successful in terms of flexibility and budget expenditure. When users are heterogeneous, the aggregator should classify users in groups of similar characteristics for maximizing his revenue profit without increasing his budget. The more diverse the user groups are, the stronger the advantage of discriminating them. The “strict” constraint on the total budget for DR incentives should be considered in practical cases, as opposed to the “loose” one, because it leads to a robust incentive policy with acceptable rewards for the users, despite the somewhat lower total flexibility attainable. When the flexibility is resold in the market, the maximum provider profit can be accomplished with a significant benefit for the user, so that both sides are satisfied. As a future work, we intend to validate our findings and the proposed learning approach for flexibility management with real users.

3.2 Practical issues for applying incentives

3.2.1 Greek Pilot Setup and User Engagement

HERON primarily focused its recruitment effort on HERON and GEK TERNA (owner company) employees, gradually expanding to friends and family. The standard equipment consists of Shelly 1 phase or 3 phase smart meter, depending on the participant's installation and a Schneider relay to remotely control water boilers for users that have them in their households. However, user screening has shown that the numbers of users with water boilers is in the range of 10-15, with even less willing to allow the platform to remotely access it. To compensate that, it was decided to install smart plugs (Shelly Plug and Plug S) in order to monitor loads of specific appliances which could be integrated in iFlex assistant.

Recruitment is an ongoing process to highlight three aspects of energy savings and efficiency gains associated with participation in HERON's Smart Energy Platform: i) know where your energy comes from, ii) know how much energy heavy appliances consume and iii) know how consumption is distributed within day/ week in addition to mentioning that all equipment, installation and maintenance costs would be covered by HERON.

Following initial feedback from users and collaboration with the organisation's marketing team, new material was produced, explaining in more detail the platform's features and scenarios in which consumption monitoring could lead to actual savings:

Figure 12: New material, explaining in more detail the platform's features and scenarios in which consumption monitoring could lead to actual savings

Furthermore, safety benefits where highlighted using user stories such as: "Are you tired of going back home to check if the oven is still on?" as a means of approaching users sceptic of smart / AI driven technology.

An issue that has been constantly raised in recruitment efforts was the "What is there for me" question. In the absence of Dynamic Tariffs and DSO issued and maintained Smart Meters, energy monitoring monetary benefits to energy consumers are reduced to savings that occur by turning off their appliances. Naturally, it has been expected by the users, that load shifting actions which may alter their schedules will have to generate direct benefits, either through a dynamic tariff that implicitly incentivises them to consume at off-peak market hours, or through an explicit payment as a reward for their actions. However, monetisation of consumption can only be based on DSO issued meters, which cannot be tampered by law (RAE Decision on Electricity Theft 404/2015) (OGGG, 2015). The smart meters installed by HERON are not covered by the aforementioned legal provisions due to technical and regulatory reasons; most notably, the liberalisation of the Greek electricity sector, which forbids Utilities (Energy Suppliers) undertaking Distributor (DSO) roles, therefore direct measures cannot be implemented. This issue had to be communicated to potential and existing iFLEX participants, given that discussions on promoting RES energy by shifting consumption in hours dominated by RES generation have been side-lined by the discussion on monetary gains, and while we expect that user participants will be supportive to some extent, their continuous engagement is not guaranteed.

In this context, we have identified the main properties the incentive mechanism should have in order to keep users engaged on a weekly / monthly basis and be compliant with regulatory constraints and company policies. Therefore, rewards should in-principle:

1. Be non-monetary
2. Reflect energy costs for requested actions i.e. for activated assets that were not scheduled for the day
3. Be given to multiple winners
4. Guarantee that all users feel that they are included and that they could win a reward
5. Reflect effort for users i.e. more active users should have more chances of winning rewards

The aforementioned properties should reward those who are more aligned with iFA actions while also not explicitly penalise more casual users. While a mechanism that could satisfy the properties is outlined in Section 3.3, specifics such as the period it will cover, price value, number of winners are yet to be clarified, while initial discussions within the consortium have identified the need to bridge the effectiveness of the incentive instrument with business actions. For example, literature suggests that a single winner over a longer period brings stronger incentives than multiple winners during shorter periods, that is although in expectation the prize is the same, risk seeking users would be more engaged if the prize is higher.

Finally, a weekly report is currently under design, showing basic consumption characteristics such as consumption broken down by day and the carbon footprint of consumption on hourly basis. This report will be further enhanced with iFA specific data, providing the accumulated scores, monetary rewards (if any) etc. In addition, as a means of boosting engagement, it will be shown that increasing actions by even a small percentage can significantly increase the score, therefore increase the probability of winning the lottery. Likewise, it will be shown that following more iFA actions could have potentially reduced the user's carbon footprint.

3.2.2 Personal, social and moral incentives

Personal, social and moral incentives are deployed in the recruitment and engagement activities (information material, interface design and performance reports) of pilot participants.

In terms of personal incentives, which cover both monetary and non-monetary elements, the visualisation of consumption, which enables participants to 'know where your energy comes from', 'how much heavy appliances consume' and 'how consumption is distributed' generates an awareness and feeling of being in control, being smart, and perhaps even an energy frontrunner. The feeling of being in control is further enforced with the aspect of feeling safe by the addition of user stories ("Are you tired of going back home to check if the oven is on?") which speak to the common human experience of responsibility. The illustration of how energy monitoring can lead to energy savings and the gaining of points to win lotteries help boost the sense of being competent and effective. Finally, the sense of feeling important and influential is also invoked since all equipment, installation and maintenance costs are offered in exchange of participation.

In terms of social incentives, participants will be able to see how their actions have helped reduce the carbon footprint and receive information regularly on the positive consequences of total participation (acceptance of events) on RES integration in their local, regional and/or national context. This knowledge evokes a sense of contributing to society and a feeling of doing the right thing.

Information given to the participants will also touch upon moral incentives (how am I doing and am I doing enough) through tracking participation and progress. It will involve visualisation of or information on: performance in terms of points and participation rate compared to others; the amount of energy saved/reduced for a given period and/or per event and/or as per personal goal set; environmental consequences of actions/participation in events and the consequences of their actions/participation in events in relation to grid security, grid stability, and RES supply integration.

3.2.3 Flexibility measurement and verification

A concrete Measurement and Verification plan is crucial in order to validate the participation of end users to Demand Response (DR) events. Within the context of the Greek pilot, explicit DR – both automated and manual – will be considered.

In explicit DR events, potential participants are requested to shift the consumption of certain flexible assets in a specific way. The specifications of the flexible assets – as well as the capacity of the pilots to measure their consumption – is crucial for validating the offered flexibility by the users. In iFLEX project, all the flexible assets within the residential pilot users' premises will be equipped with dedicated metering devices, so that the exact consumption of these assets can be directly measured. These metering data per asset can be exploited in order to validate that the requirements within the context of explicit DR events have been fulfilled. A pre-requisite for this validation is the knowledge of the type and rated power of the flexible asset, as well as its different operating states (i.e. there are more possibilities than just the on/off states). Comparing the requested flexibility (for accepted DR events) and the measured state of the device, the users' conformance to the requested action can be elaborated, but also their responsiveness to DR activities. As regards automated DR, boilers, which shall be controlled via relays and equipped with dedicated sub-meters, will be the targeted flexible assets. On the other hand, based on the most recent information, manual DR will focus mostly on air-conditioning units. The actual consumption of these units will be measured thanks to dedicated smart plugs. Their metering data will be exploited for the verification of users' conformance to the DR events' requirements.

3.2.4 Estimation of total flexibility desired by RES Aggregator and economic implications

The total flexibility desired by RES Aggregator will be directly used to mitigate uncontrollable RES generation imbalances. In other words, the ultimate goal is to minimize the deviations between the actual RES generation with respect to the declared generation schedule of the RES portfolio involved in the Day-Ahead Market (i.e. DAM schedule). In practical terms, in case that the RES portfolio generates in real-time more (less) than the declared DAM schedule (due to inherent forecasting errors), then the end-user DR resources will be called to increase (decrease) their consumption in order to collectively mitigate RES generation imbalances.

For the estimation of the total flexibility desired by the RES Aggregator, every 15-min RES Aggregator foresees which is the said total flexibility (positive/negative) that will be needed to be provided by DR Aggregator during the next 15-min interval (on the basis of the cleared DAM schedule and relevant very short-term forecasts that are continuously made by RES Aggregator during the course of the day), so that RES generation imbalances are counterbalanced as much as possible. The exact number and maximum capacity of the RES (PV) plants that consist the said RES portfolio shall be indirectly determined by the attained number of end-user households that will be actively engaged during the course of the project. This serves the need to obtain comparable RES and end-user DR portfolios in terms of aggregated capacity, so that more realistic flexibility requests are formulated.

Regarding the economic implications, in principle RES Aggregator is supposed to participate in a centralized wholesale market where the "dual-pricing" option is adopted as regards the imbalance pricing. According to this pricing scheme, in case a BRP (e.g. said RES Aggregator) is short (i.e. it produces in real-time less than its DAM schedule), for its production deficit it pays to the TSO the marginal price of all accepted upward balancing offers (MPu) that have been provided by the BSPs in the balancing market, which is normally higher than the respective DAM clearing price (MPu > DAM price). On the contrary, in case a BRP is long (i.e. it produces in real-time more than its DAM schedule), for the excess generation it is paid by the TSO the marginal price of all accepted downward offers (MPd) that have been provided by the BSPs in the balancing market, which is normally lower than the respective DAM clearing price (MPd < DAM price). In this way, the BRP has no incentive to over-/under-declare its forecasted generation in the DAM. This, in turn, mitigates the possibility that gaming behaviours appear in the day-ahead and balancing market by all participants (BSPs and BRPs).

In the above context, in general a bilateral contract could be concluded between the RES Aggregator and the DR Aggregator for the financial settlement of the bilateral mitigation of the aforementioned RES generation imbalances. The detailed terms of this contract can be decided mutually by the involved parties (DR and RES Aggregator). A possible contract scheme could be the following: the total flexibility desired by the RES Aggregator for every 15-min interval (in MWh) and which must be provided by the DR Aggregator is priced at a fixed price (€/MWh), which may be different for positive and negative imbalances. For instance, the fixed contract price when DR Aggregator addresses RES portfolio short imbalances (i.e. RES generation in real-time is less than DAM schedule and, therefore, DR resources are called to decrease their consumption to mitigate RES generation imbalances) lies between the DAM clearing price and the MPu. On the contrary, the fixed contract price when DR Aggregator addresses RES portfolio long imbalances (i.e. RES generation in real-time is higher than DAM schedule and, therefore, DR resources are called to increase their consumption, accordingly) lies between the MPd and the DAM clearing price. Average historical clearing prices could be used for the pilot implementation of this bilateral contract scheme. An appropriate penalty scheme could also be included in the aforementioned contract scheme in case DR Aggregator does not fulfill its contractual obligations towards the RES Aggregator. For instance, this may occur if the RES Aggregator is long in real-time and the DR Aggregator is not capable of activating (i.e. turning-on) as many end-user DR resources as needed (or agreed, according to the terms of the said bilateral contract) to counterbalance RES generation imbalances.

Although the aforementioned contract scheme is the "appropriate" one in practice, for tractability reasons in the modelling part above (see section 3.1.3.3), a simpler version was considered, where only positive flexibility requests are remunerated and no penalties for non-fulfilment of the associated DR Aggregator obligations are imposed.

3.3 Combination of economic and non-economic incentive mechanisms

Next, we develop the specific mechanism awarding the incentives to the users of the Greek pilot.

Ideally, user n, if targeted for a DR event and participating successfully, he should be awarded in money the incentives r_n initially offered to him when targeted. Recall, that participation of user n in a DR event actually happens with probability $p_n(r_n)$ given by equation (1). Therefore, in a longer period (say one month) user n should be awarded the sum of rewards across the set of DR events where he participated successfully; for simplicity, we denote this amount as R_n. This mechanism, namely direct payment of such an amount to the user, *cannot* be implemented due to constraints of the Greek pilot partners. For the same reason, an equal discount to the user's energy bill cannot be granted either.

The "closest" incentive mechanism is for user n to receive a gift, namely, an item of value R_n. This mechanism would involve the same expenditure for the provider. However, if the value of the gift is low, the award of such a gift may *not* be attractive for the user. The same applies, to a certain extent, for the earning of a low monetary amount R_n. According to prospect theory (D5.2, 2021), it is preferable for the user to be offered (as an incentive) a *prospect* of receiving a gift of considerably higher value, by participating in a *lottery*. Next, we discuss and assess a set of such lottery mechanisms.

First, it should be noted that the rewards offered to users for participating in DR events still apply and are still calculated by the same optimization problems already analyzed. However, these rewards now correspond to virtual currency (or "points"), which at the end of the period considered are *converted* to the probability $w_n(R_n)$ for each of the users to win the lottery, given that he is awarded a total amount R_n of rewards. (For simplicity, we maintain the term "reward", rather than "virtual reward" or "points".) Of course, if points are calculated somewhat differently (e.g. if additional points are offered in certain cases, as a result of the provider's policy to promote certain actions), then the propositions below still apply.

A first desirable property of the mechanism at large is that $w_n(R_n)$ is proportional to R_n, in order for users to be incited to participate in DR and collect rewards. This leads us to the first proposition for a mechanism; namely, to perform a lottery of a single item of pre-specified value V, with each user having a probability of winning $w_n(R_n)$ that is proportional to his total reward R_n. Since one of the users should always win the lottery, there should hold $\sum_j w_j(R_j) = 1$, which implies that:

$$w_n(R_n) = \frac{R_n}{\Sigma_j R_j} \tag{18}$$

Note that the "running" index in the summation spans the set of all users. This essentially corresponds to the simple incentives' mechanism presented in Subsection 3.2.1, which is practically applicable.

However, this straightforward mechanism has a somewhat surprising disadvantage. If all N users are symmetric, then they will all have (on the average) the *same* probability $1/N$ of winning the lottery regardless the rewards gained, and thus regardless the flexibility offered. In other words, a population of N symmetric users contributing high flexibility in (say) the first period and low flexibility in the second period will be treated the same in both cases by the mechanism. This fact can incite users to contribute with low flexibility, which is *not* the right incentive.

The reason for the aforementioned undesirable property is the normalization of the probability of winning $w_n(R_n)$, which introduces an interdependence among the users. Therefore, we can circumvent this problem by organizing a ***personal*** lottery for each user. In particular, the probability $w_n(R_n)$ for user n to win his lottery should depend on its rewards only, in such a way that the ***expected value*** of the payoff earned by the user equals his total amount R_n of rewards. Thus, in a series of periods, the user will be compensated on the average as much as in the case of monetary incentives. Therefore, in the first place, it is ***not*** necessary to run additional experiments to assess this mechanism, and characterize the optimal outcomes, their properties etc. Nevertheless, the effect of the user's prospect for a prize of high value, can be assessed in future experiments; it is plausible that it improves the participation probability and thus the expected incentives of the provider for a given flexibility target. Furthermore, if the item put in user's n personal lottery has a particular high value V, then we can meet the desired expected reward by tossing a biased coin (i.e. by performing a Bernoulli trial), with "success" probability $w_n(R_n) = min\{R_n/V, 1\}$. If "success" is not the outcome, then the item is not awarded to user n.

This set of N *independent personal lotteries* is a simple and mathematically sound mechanism that provides the right incentives to each of the users, regardless the contribution of others. However, the actual total expenditure of the provider can *vary* considerably. One extreme value of this expenditure arises when no user wins in his personal lottery, and thus the total expenditure of the provider is 0; this event applies with probability $\boldsymbol{\Pi_j}\,(1 - w_j(R_j))$. However, such a case may not be desirable from a publicity point of view and may also give rise to doubts on the credibility of the lotteries' process. The opposite extreme case arises when all users win in their personal lotteries, and thus the total expenditure of the provider is very high (namely $N \cdot V$), which is not desirable from an economic point of view; this event applies with probability $\boldsymbol{\Pi_j}\, w_j(R_j)$. Therefore, we do not opt for this mechanism either.

From the above discussion, it is evident that the desired properties of the lottery mechanism at large are as follows:

- only one lottery with all users is performed;
- each user n has an expected payoff equal to his total amount R_n of rewards;
- exactly one user wins, so that the provider's total expenditure is predictable.

These three objectives can be attained simultaneously only if we run a single lottery with all users, where:

- each user has a probability of winning $w_n(R_n)$ that is proportional to his total reward R_n,
- all probabilities of winning sum to 1, so that we always have exactly one winner, which implies that for each user n we have $w_n(R_n) = R_n \,/\, \Sigma_j R_j$,
- and the value of the item that constitutes the prize of the lottery is *not* predetermined (otherwise, as already explained we do not offer the right incentives to the users), but
  is equal to the total rewards $\Sigma_j R_j$ given by the provider to all users in this period.

Indeed, the expected payoff of user n equals the product of the probabilities of winning of user *n* times the value of the item put in lottery, that is $w_n(R_n) \cdot (\Sigma_j R_j)$, which equals R_n. That is, by setting the value of prize of the lottery as equal to the total rewards $\Sigma_j R_j$, which depends on the user responsiveness to DR, rather than to an arbitrary pre-specified value (as in the initially considered lottery) the mechanism provides the right incentives to the users. Therefore, again, in the first place, it is ***not*** necessary to run additional experiments to assess this mechanism, and characterize the optimal outcomes, their properties etc. However, the practical implementation of this mechanism entails that the value of the item put in lottery (and thus the item itself) is determined *after the end* of the period considered on the basis of all rewards offered to the users. Thus, for this decision to be accountable, all such rewards should be announced, in an anonymized yet auditable way, so that each single user can verify that the provider does not undermine the value of the item put in lottery.

Variations of the basic mechanism:

- In order for multiple users to benefit from the lottery mechanism, the provider can put in lottery multiple (say 2-3) items, with total value equal to $\Sigma_j R_j$. This may be preferable for the provider, since users can possibly be more eager to participate if they have multiple chances to win. When the same formula is employed for the probability $w_n(R_n)$ of user n winning each particular lottery, the expected payoff of user n still equals R_n provided that a user that wins the first lottery is allowed to also participate in the second one etc. On the contrary, if each user is allowed to win at most one item, then the expected payoff of user n is lower than R_n. Indeed, to illustrate this fact, suppose that two items of equal value, namely $\frac{1}{2} \cdot \Sigma_j R_j$, are put in lottery. Then, the expected payoff of user n in the first lottery is $w_n(R_n) \cdot \left[\frac{1}{2} \cdot \Sigma_j R_j\right] = \frac{1}{2} \cdot R_n$, while that in the second lottery is $w_n(R_n) \cdot [1 - w_n(R_n)] \cdot \left[\frac{1}{2} \cdot \Sigma_j R_j\right] = \frac{1}{2} \cdot R_n \cdot [1 - w_n(R_n)]$. Therefore, the total expected payoff of user n now equals $R_n \cdot [1 - \frac{1}{2} \cdot w_n(R_n)]$, which is somewhat lower than R_n. Despite this property, putting multiple items on lottery has another nice property: the provider can resort to a tiered determination of the prizes put in lottery: the provider can announce (in the beginning of the period) the value V_0 of the “basic” item to be put in lottery (at the end), and the value V_1 of an additional item to be also put in lottery if $\Sigma_j R_j > R^*$, and the value V_2 of a third item to be also put in lottery if $\Sigma_j R_j > R^{**}$, where $R^{**} > R^*$, etc. That is, the values of the items to be possibly put in lottery are pre-specified, and only the exact set of such items is determined at the end of the corresponding period.

- Instead of employing the (virtual) rewards and tickets, the probability $w_n(R_n)$ of (each) user n winning the lottery is set proportional to his total flexibility X_n offered in the period of interest, which serves (as a proxy for R_n). In this case, the total value of the item(s) put in lottery should be *proportional* to the total flexibility $X = \Sigma_j X_j$ attained by the provider during this period. Although the incentives offered to users by this lottery mechanism are only “approximately right”, the mechanism itself can be easier to explain to users. In this case, *it is necessary* to run additional experiments to assess this mechanism, and characterize the optimal outcomes, their properties etc., by introducing the probability of winning (which depends on the flexibility) in the objective functions etc.

4 Incentive mechanisms for the Slovenian pilot

4.1 Modeling and analysis of economic incentive mechanisms

4.1.1 The Context

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. 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.

4.1.2 The Model

We consider a set $\mathcal{N}$ of N consumers. Each day is divided into T time slots, indexed by t. For each consumer $n \in \mathcal{N}$, we denote as $\boldsymbol{x}_{n,0}$ the daily vector of baseline energy consumption per time slot prior to DR. Moreover, we assume that some customers possess solar panels, which generate some amount of electricity. We denote as $\boldsymbol{w}_n = \{w_n^t\},\ \forall t \in T$ the energy generation vector of the solar panels of prosumer n.

4.1.2.1 The DR Aggregator's problem

We denote as x_n^τ the flexibility offered by consumer n at time slot τ. We assume that each consumer n is compensated according to a linear incentives' policy. That is, he receives by the DR aggregator incentives r_n per flexibility unit provided thereto. Then, the objective of the DR aggregator is to select the appropriate set of consumers and the flexibility x_n^τ to be asked by each of them, so that the required flexibility X^τ is met at a specific time slot of interest τ with the minimum amount of incentives offered. Please note that $\boldsymbol{x}_{n,0} = \{x_{n,0}^t\}, \forall t \in \mathcal{T}$ denotes the baseline daily consumption for consumer n, while $\boldsymbol{x}_{n,1} = \{x_{n,1}^t\}, \forall t \in \mathcal{T}$ is the updated daily consumption schedule for consumer n subject to the flexibility event. Therefore, the DR aggregator's optimization problem is as follows:

$$\textbf{Minimize:} \sum_{n\in\mathcal{N}} r_n y_n x_n^\tau \tag{19}$$

$$\textbf{s.t.} \sum_{n\in\mathcal{N}} y_n x_n^\tau \geq X^\tau \tag{20}$$

$$\begin{aligned} & y_n\Big(r_n x_n^\tau + U_n(\mathbf{x}_{n,0} - \mathbf{x}_n) - U_n(\mathbf{x}_{n,0}) \\ & - \sum_{t\in\mathcal{T}, x_{n,0}^t - x_n^t \geq w_n^t} (x_{n,0}^t - x_n^t - w_n^t)\psi^t + \sum_{t\in\mathcal{T}, x_{n,0}^t \geq w_n^t} x_{n,0}^t \psi^t \\ & + \sum_{t\in\mathcal{T}, 0 < x_{n,0}^t - x_n^t < w_n^t} (w_n^t - x_{n,0}^t + x_n^t)\phi^t \\ & - \sum_{t\in\mathcal{T}, 0 < x_{n,0}^t < w_n^t} (w_n^t - x_{n,0}^t)\phi^t\Big) \geq 0,\ \forall n \in \mathcal{N} \end{aligned} \tag{21}$$

$$x_n^\tau \leq x_{n,0}^\tau + w_n^\tau,\ \forall n \in \mathcal{N} \tag{22}$$

where $y_n \in \{0,1\}$ is the decision variable for targeting user n. ψ^t is the electricity unit price at time slot t, while φ^t is the feed-in tariff for injecting renewable energy into the network which can be different per time slot t. Recall that no other kind of energy trading is assumed to take place. Note that $\widetilde{x_n}^\tau$ is the $\tau - th$ component of the vector $x_{n,0} - x_n$. Constraint (21) is an incentive compatibility condition, which ensures that each targeted user will indeed offer the flexibility requested thereby, because he is better-off in terms of net benefit than by not participating in DR. Also, constraint (22) is a feasibility condition for flexibility provision that dictates flexibility per user to be upper bounded by the sum of his baseline energy consumption and his solar energy production at time slot τ.

To simplify our problem, we henceforth consider a simpler DR incentives policy. In particular, we assume that all users are offered the same incentive r, per flexibility unit, while all users can offer flexibility (i.e., there is no targeting). This amounts to a practically applicable DR incentives policy, with all consumers being eligible and the common per unit incentives being publicly announced by the DR aggregator. In this case the formulation of the DR aggregator's optimization problem becomes:

$$\textbf{Minimize:} \sum_{n\in\mathcal{N}} r x_n^\tau \tag{23}$$

$$\textbf{s.t.} \sum_{n\in\mathcal{N}} x_n^\tau \geq X^\tau \tag{24}$$

$$x_n^\tau \leq x_{n,0}^\tau + w_n^\tau,\ \forall n \in \mathcal{N} \tag{25}$$

$$\begin{aligned} & r x_n^\tau + U_n(\mathbf{x}_{n,0} - \mathbf{x}_n) - U_n(\mathbf{x}_{n,0}) \\ & - \sum_{t\in\mathcal{T}, x_{n,0}^t - x_n^t \geq w_n^t} (x_{n,0}^t - x_n^t - w_n^t)\psi^t + \sum_{t\in\mathcal{T}, x_{n,0}^t \geq w_n^t} x_{n,0}^t \psi^t \\ & + \sum_{t\in\mathcal{T}, 0 < x_{n,0}^t - x_n^t < w_n^t} (w_n^t - x_{n,0}^t + x_n^t)\phi^t \\ & - \sum_{t\in\mathcal{T}, 0 < x_{n,0}^t < w_n^t} (w_n^t - x_{n,0}^t)\phi^t \geq 0,\ \forall n \in \mathcal{N} \end{aligned} \tag{26}$$

This optimization problem can be solved by the aggregator w.r.t. r, $x_n, \forall n \in \mathcal{N}$ when the DR aggregator has full information concerning the utility functions. That is, $U_n(\cdot)$ is known by the aggregator for each customer n. Otherwise, we have to resort to a distributed and iterative solution, which is described in the distributed algorithm section. In that case, the aggregator solves the optimization problem of equation (23) considering only the constraints (24) & (25), while the user solves his own optimization problem, which is introduced in the user's problem section.

4.1.2.2 The User's problem

We assume that users are offered by the DR aggregator incentives r per flexibility unit at time slot τ. Then each user n has to select is optimal flexibility vector x_n, by solving the following problem:

$$\begin{aligned} & \textbf{Maximize: } r x_n^\tau + U(\mathbf{x}_{n,0} - \mathbf{x}_n) - U_n(\mathbf{x}_{n,0}) \\ & - \sum_{t\in\mathcal{T}, x_{n,0}^t - x_n^t \geq w_n^t} (x_{n,0}^t - x_n^t - w_n^t)\psi^t + \sum_{t\in\mathcal{T}, x_{n,0}^t \geq w_n^t} x_{n,0}^t \psi^t \\ & + \sum_{t\in\mathcal{T}, 0 < x_{n,0}^t - x_n^t < w_n^t} (w_n^t - x_{n,0}^t + x_n^t)\phi^t \\ & - \sum_{t\in\mathcal{T}, 0 < x_{n,0}^t < w_n^t} (w_n^t - x_{n,0}^t)\phi^t \end{aligned} \tag{27}$$

For user n to participate in DR, two conditions should hold:

- Individual Rationality (IR): The net benefit from participating in DR should be positive.
- Incentive Compatibility (IC): The net benefit from participating in DR should be higher than that when not participating, or equivalently the difference of these two net benefit values should be non-negative; this amounts to condition (26).

Since $x_{n,0} > 0$ for a user n, his net benefit when not participating in DR is positive. Thus, IR and IC conditions are concurrently met when condition (26) is true.

Our analysis to follow is applicable to increasing and differentiable user utility function. Nevertheless, in our analysis, we employ the following utility $U(\cdot)$:

$$U_n(\mathbf{x}_n) = \sum_{t \in \mathcal{T}} \beta_n^t (x_{n,0}^t - x_n^t) \tag{28}$$

where $\beta_n^t = x_{n,0}^t / \max\{x_n\}$. According to this function, a reduction (resp. increase) in energy consumption in a certain slot results in loss (resp. gain) of comfort, and thus of utility, for the user. These utility deviations are summed in a weighted fashion over the entire time period T considered, with a normalized weight per slot that is proportional to the total energy consumption during that slot.

4.1.2.3 Equilibrium

The aforementioned problems, in fact, can jointly be seen as of a Stackelberg (leader-follower) game: the DR aggregator moves first to select incentives r and each user n follows by selecting his flexibility x_n. The overall optimization problem (comprising DR aggregator's and user's ones) can be solved by means of backwards induction. That is, the user's problem is solved first for each user n, to find the optimal flexibility x_n, assuming that optimally chosen incentives r^*, applicable for the entire population of users, have been announced by the DR aggregator. Then, the DR aggregator's problem could be solved, if the dependence of $x_n, \forall n \in \mathcal{N}$ to r^*, were known expressed in closed form. However, this is a very restrictive assumption. Hence, we resort to an iterative distributed algorithm for deriving the desired equilibrium point.

4.1.2.4 Distributed Algorithm

As already explained, in the case where user utility functions are not known, then the DR aggregator and the user should solve their individual problems, i.e., (23) s.t. (24) & (25) for the DR aggregator and (27) for the user respectively. For this purpose, we introduce the following iterative distributed approach: The DR aggregator and the consumers jointly compute an equilibrium based on a gradient algorithm (Hannah, 2015), where (i) the DR aggregator sets the reward per flexibility unit and (ii) each prosumer solves his own maximization problem in response. In all cases studied, the iterative process converged to the optimal solution; no case of divergence was observed.

At the beginning of each round k, the DR aggregator announces the per unit of flexibility incentives r. Each user n updates his offered flexibility x_n' according to the formula below and announces it to the DR aggregator.

$$\begin{aligned} x_n^{t,k+1} = \min\{ & x_{n,0}^t,\ x_n^{t,k} + \xi(r^k + (-\beta^t) + \\ & \psi^t \mathbf{1}(x_{n,0}^t - x_n^t - w^t) - \phi^t \mathbf{1}(w^t - x_{n,0}^t + x_n^t)\} \end{aligned} \tag{29}$$

$\mathbf{1}(\cdot)$ is an indicator function, which equals 1 if its argument is greater than zero, or 0 otherwise. Then, DR aggregator updates the per unit of flexibility incentives r according to the formula below.

$$r^{k+1} = \max\left\{ r^k + \xi\left(X^\tau - \sum_{n \in \mathcal{N}} x_n^\tau \right),\ 0 \right\} \tag{30}$$

At the end of the round, the DR aggregator sets $r = r'$ and each customer $n \in \mathcal{N}$ sets $x_n = x_n'$.

4.1.2.5 Multiple Flexibility Slots

We now consider the case that the aggregator requests flexibility in multiple time slots S. One may argue that this problem can be solved by consecutively solving problem (23) for each of the time slots of interest. However, such a solution would only be suboptimal, as the flexibility provided separately per time slot would only be "myopic" without being able to find the updated consumption schedules that joint satisfy the flexibility objectives. The multi-slot aggregator problem is given by:

$$\textbf{Minimize:} \sum_{\tau \in \mathcal{S}} \sum_{n \in \mathcal{N}} r x_n^{\tau} \tag{31}$$

$$\textbf{s.t.} \sum_{n \in \mathcal{N}} x_n^{\tau} \geq X^{\tau} \text{ ,} \forall \tau \in \mathcal{S} \tag{32}$$

$$\begin{aligned}
& r \sum_{\tau \in \mathcal{S}} (x_n^{\tau}) + U_n(\mathbf{x}_{n,0} - \mathbf{x}_n) - U_n(\mathbf{x}_{n,0}) \\
& - \sum_{t \in \mathcal{T}, x_{n,0}^t - x_n^t \geq w_n^t} (x_{n,0}^t - x_n^t - w_n^t)\psi^t + \sum_{t \in \mathcal{T}, x_{n,0}^t \geq w_n^t} x_{n,0}^t \psi^t \\
& + \sum_{t \in \mathcal{T}, 0 < x_{n,0}^t - x_n^t < w_n^t} (w_n^t - x_{n,0}^t + x_n^t)\phi^t \\
& - \sum_{t \in \mathcal{T}, 0 < x_{n,0}^t < w_n^t} (w_n^t - x_{n,0}^t)\phi^t \geq 0, \ \forall n \in \mathcal{N}
\end{aligned} \tag{33}$$

4.1.3 Additional incentives

4.1.3.1 Peer pressure through social comparison

One behavioral driver for reducing power consumption is peer pressure through social comparison. Peer pressure can be exercised for flexibility management simply by privately announcing to the user the relative performance percentile to which he falls according to his offered flexibility in a number of previous DR events. We can assume that the user enjoys some personal *satisfaction* h_i from being ranked first. The higher the flexibility offered by the user at the time duration of interest, the higher the probability that this user is ranked first. We approximate that probability below.

First, we remind some material from the theory of order statistics (David, 2011). Let $X_1, \ldots, X_{N-1}$ be $N-1$ independent and identically distributed (i.i.d.) random variables. In our case, the random variable X_j denotes the energy flexibility of user j. The order statistics $X_{(1)}, X_{(2)}, \ldots, X_{(N-1)}$ are also random variables, defined by sorting the realizations of $X_1, \ldots, X_{N-1}$ in non-decreasing order. Namely, for each realization ω, we arrange the sample values $X_1(\omega), \ldots, X_{N-1}(\omega)$, in non-decreasing order, $X_{(1)}(\omega) \leq X_{(2)}(\omega) \leq \cdots \leq X_{(N-1)}(\omega)$, where $(1), (2), \ldots, (N)$ denote that permutation of indices $1,2, \ldots, N-1$ for which the random variables X are ordered. Thus, we have:

$$\begin{aligned}
X_{(1)} &= \min\{X_1, \ldots, X_{N-1}\} \\
&\vdots \\
X_{(N-1)} &\equiv \max\{X_1, \ldots, X_{N-1}\} \,.
\end{aligned} \tag{34}$$

For a user n to be ranked first, it is necessary and sufficient that his flexibility x if higher than the maximum flexibility of all $N-1$ other users. For a fixed value of x, this probability is given by:

$$\begin{aligned}
F_{X_{(N-1)}}(x) &= Prob(\max\{X_1, \ldots, X_{N-1}\} \leq x) \\
&= |F_X(x)|^{N-1}
\end{aligned} \tag{35}$$

Where $F_X(\cdot)$ is the common cumulative distribution function (CDF) of the variables $X_1, \ldots, X_{N-1}$. This CDF can be estimated based on prior flexibility performance of the users. As a simple approximation, this CDF can be assumed equal to the of the baseline consumption of the users in the flexibility slot scaled by $X/\sum_{n\in\backslash} x_{n,0}$, which is the factor by which the total consumption is discounted due to offering of flexibility. The term $F_{X_{N-1}}(\widetilde{x_n}) \cdot h_n$ is the average benefit of a user n from being ranked first when exerting flexibility $\widetilde{x_n}$. This term should be added to the user problem (27) to express the incentives by the mechanism of peer pressure.

4.1.3.2 Lotteries

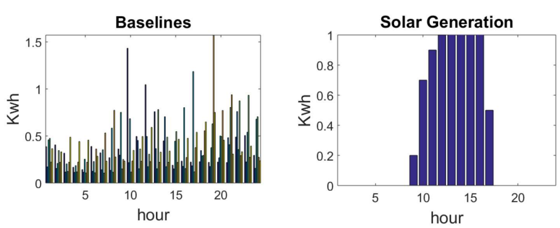
According to prospect theory (Kahneman, 1979), when presented with alternatives that involve risk and uncertainty, people tend to prefer higher gains with small probability than equivalent (on the average) gains with certainty. Flexibility rewards cannot always be easily implemented due to significant changes required to the billing system and complexity for their inclusion in the accounting records of the utility company or aggregator. Alternative to the flexibility rewards, albeit with simpler implementation in practice, could be the organization of weekly/monthly lotteries for flexibility with a certain price of higher value V. The higher the participation of the user to flexibility events and the higher the flexibility offered, the higher the probability to win the lottery. This could be achieved in practice by providing a number of lottery tickets to each user that is proportional to the flexibility he offers over a certain period. Then, a ticket would be drawn from the lottery to determine the winner of the particular period. A new lottery would subsequently be started for the next period. The probability for a user to win the lottery is proportional to his individual flexibility over the sum of total flexibility provided by all users. However, according to prospect theory, since the probability p to win a high-valued prize is low, the satisfaction of a user from this prize is given by $\pi(p) \cdot V > p \cdot V$; this is referred to as “hope of large gain”. As compared to the reward per flexibility unit, a lottery can be more motivating for flexibility management for the same incentive cost.

4.1.4 Evaluation

We employed the REDD dataset (Kolter, 2011). The baseline consumption of the houses is depicted in Figure 13a. We assume that the requested flexibility is 2KWh at the time slot of 12pm-1pm. We consider that the off-peak tariff per electricity unit is 0.1 €/KWh, while the peak tariff, employed between 12pm-1pm, becomes 0.4€/KWh. We assume that the utility function (28) expresses the satisfaction for user n from his consumption schedule. We assume the parameter $\xi = 0.01$ in the distributed algorithm of the distributed algorithm section.

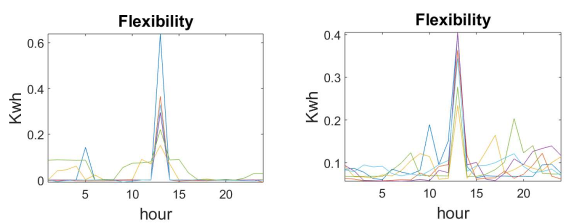
For peak-tariff pricing at the time slot of the desired flexibility without any flexibility rewards ($r = 0$), the optimal solution to problem (23) is depicted in Figure 14a, while its decentralized solution is depicted in Figure 14b. Observe that flexibility distributions are aligned, i.e., Pearson correlation was found to be 0.75. However, in the decentralized solution, there are some rebound effects regarding consumption in the other time slots. The decentralized solution has converged in 46 iterations.

If no peak-tariff pricing is employed, but flexibility rewards are in order, then the desired flexibility is obtained (cf. Figure 15a) at a cost for incentive rewards (cf. Figure 15b). The total amount of rewards given is 1.47€ for this flexibility event. The flexibility distribution from optimal rewards is almost the same with that of Figure 14a, i.e., Pearson correlation coefficient is 0.974, while total flexibility is 2KWh in both cases, which means that the users offer the same flexibility regardless of the exact incentive mechanism employed, i.e., peak-tariff pricing or rewards. In Figure 15b, we also compare the optimal rewards with those resulting from the distributed algorithm. The distribution of rewards per user from the distributed algorithm is smoother than the optimal one, while the total cost of incentives is slightly higher than optimal, i.e., 1.68€, as expected.



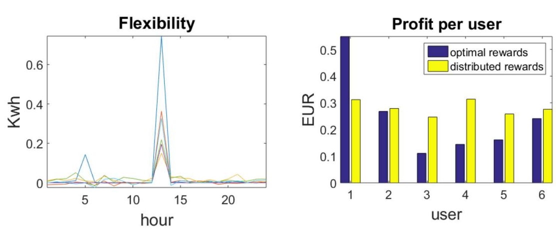
(a) (b)

Figure 13: (a) The baseline consumption. (b) PV power generation hourly schedule per prosumer.



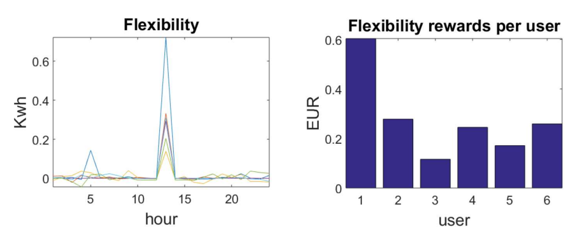
(a) (b)

Figure 14: Peak-tariff pricing: (a) Optimal flexibility per user. (b) Flexibility per user with the distributed algorithm.



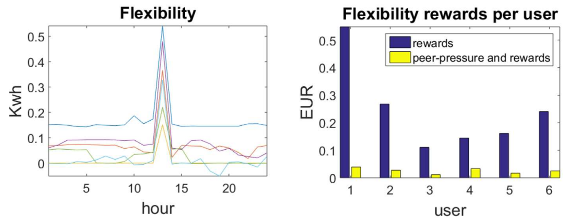
(a) (b)

Figure 15: Flexibility rewards: (a) Optimal flexibility per user; (b) Flexibility profit per user with optimal and suboptimal (distributed) rewards.



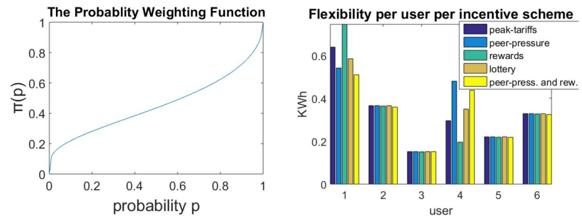
(a) (b)

Figure 16: PV power generation: (a) Optimal flexibility per user, (b) given specific flexibility rewards.



(a) (b)

Figure 17: (a) Optimal flexibility per user with peer pressure. (b) Flexibility rewards per user when rewards are combined with peer pressure.



(a) (b)

Figure 18: (a) A probability weighting function π. (b) Comparison of optimal flexibility per user with different incentive schemes.

(a) (b)

Figure 19: (a) Optimal flexibility rewards per time slot employing (a) multi-slot optimization, (b) consecutive myopic optimizations per time slot.

We now consider the case of solar power generation according to Figure 13b. We assume that net metering is employed, i.e., the feed-in tariff is 0.1 €/KWh. When flexibility rewards are employed instead of peak-tariff pricing, then the flexibility provided by the users and their respective rewards are higher, as depicted in Figure 16a and Figure 16b respectively. This is because, a portion of the baseline consumption can be satisfied by the solar power, thus allowing for a higher flexibility.

We also evaluate the alternative incentive mechanisms in terms of effectiveness for flexibility management. Employing only peer pressure and assuming satisfaction from being ranked first $h_n = 1, \forall n \in N$, the flexibility offered by the users in the time slot of interest is depicted in Figure 17a. Combining peer-pressure with rewards results in lower rewards for aggregating the same amount of flexibility, as illustrated in Figure 17b.

Moreover, we employed lotteries alone assuming the lottery prize equal to the total cost for rewards per flexibility event, i.e., 1.47€, so that a fair comparison can be made. The probability weighting function (i.e., $e^{-(-\ln(x))^{0.5}}$) (Prelec, 1998) that we employed to express the user prospect with respect to the probability to win is depicted in Figure 18a. In Figure 18b, we illustrate the flexibility offered by each user with the different forms of incentive schemes (at the same cost when applicable). Next, we consider the case where the aggregator aims to find the optimal rewards in order to gather flexibility 2KWh at each of three different time slots, namely 11am-12pm, 12-1pm and 1-2pm hours. Employing the aggregate optimization approach (31), we find that the optimal reward per flexibility unit is 0.57 €/KWh. As depicted in Figure 19, the optimal rewards per user for the three time slots with the multi-slot optimization framework are lower than those that are found to be needed by employing the flexibility optimization approach (23) for each of the three time slots consecutively. Separate consecutive flexibility optimizations per time slot give optimal rewards per flexibility unit of 0.63€/KWh, 0.73€/KWh and 0.82€/KWh respectively for the three time slots. Therefore, as expected, myopic optimization of the incentives for flexibility per time slot is outperformed by the multi-slot optimization approach.

4.2 Practical issues for applying incentives

4.2.1 Dynamic network tariffs

In the area of promoting investments in smart grids, during the 2016-2018 regulatory period, the Energy Agency (the national energy regulator in Slovenia) gave for the first time the DSOs the possibility of using dynamic pricing of network fee for electricity. Implementation incentives were focused on performance testing during the current regulatory period active inclusion of users in adjustment programs using dynamic pricing - pilot critical peak tariff (hereafter PCPT) from Article 123 of the Act on Methodology for determination of network charges and criteria for determining eligible costs for electric power networks and methodology for calculating network charges (Official Gazette of the Republic of Slovenia, no. 59/10, 52/11, 81/12).

The PCPT was an experimental network tariff for the distribution system with a special tariff item for transferred working energy, which deviated from the normal tariff item and was valid for the duration of the peak network load (critical event). For the implementation of this tariff, the number of critical events in a certain period, their duration, and the time conditions for notifying customers about their occurrence were limited in advance. The PCPT was intended to dynamically shift end users from peak to off-peak system load, considering the availability of energy from renewable energy sources, energy obtained from high-efficiency cogeneration of electricity and heat, and distributed generation of electricity. The DSO had to inform the end user at least 24 hours in advance of the start and duration of the PCPT. The same information had to be published simultaneously on the DSO's website. The number of PCPT hours in the calendar year was 50. The DSO had to inform the final user, who was included in the project based on consent, about the start and duration of the calculation of the network charge according to the pilot tariff and during this period provide him with a detailed calculation of the network charge according to all tariff items. The minimum period for calculating the network fee according to the pilot tariff was one year. The PCPT tariff item occurred during a critical peak tariff period, which could be during a higher or lower tariff period.

Based on the mentioned incentives, two pilot projects in the field of adjusting electricity consumption with the help of dynamic pricing took place in Slovenia in 2017 and 2018: PREMAKNI PORABO project on the distribution area of Elektro Maribor and the European research project Flex4Grid on the distribution area of Elektro Celje.

In the regulatory period 2019-2022, for the incentives derived from the Act on the methodology for determining the regulatory framework and the methodology for calculating network fees for electricity operators (Official Gazette of the Republic of Slovenia, no. 46/18, 47/18 - cor. ., 86/18, 76/19, 78/19 – app., 85/20, 145/21 and 172/21 – ZOEE), were able to qualify pilot or demonstration projects based on dynamic pricing, which were implemented with the aim of answering key development questions regarding the active participation of customers in the market, the applicability of new technologies and services in the field of smart networks and related market mechanisms, such as using the flexibility of end users. The DSO was able to use the pilot mechanisms for calculating the network fee from Articles 135 and 137 of the Act to promote the adjustment of demand and the management of electricity consumption.

From Article 135 follows that the DSO can calculate the network fee for the distribution system based on the negative and positive critical peak tariff model, as follows:

- Positive Critical Peak Tariff (PCPT) is tariff item during peak network load (positive critical peak tariff item), which can occur during a higher daily tariff item, a lower daily tariff item or a single daily tariff item.
- Negative Critical Peak Tariff (NCPT) is tariff in times of excess production (negative critical peak tariff item), which can occur during times of higher daily tariff item (VT), lower daily tariff item (MT) or uniform daily tariff item (ET) for example during peak production from distributed energy sources (usually between 11:00 and 16:00) or during the time of minimum consumption, which can also be used by customers to charge electric vehicles at night (usually between 0:00 and 04:00).

The critical peak tariff is intended to reduce the consumption of end users at the time of critical peak load of the network, or to increase the consumption of end customers at the time of critical net production of the network, with the aim of ensuring the maximum possible load reduction of the network. The time of onset of positive or negative critical tariff items is determined by the DSO based on forecasting the operating state, taking into account environmental factors or the availability of energy from dispersed energy sources.

The DSO must effectively inform each end user and aggregator or other authorized person (if the end customer participates in the project through them) about the start and duration of the PCPT or NCPT, namely:

- must notify the end customer, whose loads are not automatically controlled, by direct notification at least 24 hours in advance before the activation of the measure;
- to the final customer, whose loads are automatically controlled (directly or indirectly through the local energy management system), forwards the demand adjustment request in accordance with the technical requirements of the technology used and the operational requirements of each measure.
- The minimum number of PCPT hours in a calendar year is 30 and the maximum is 100. The maximum possible number of NCPT hours in a calendar year is limited to 3,650.

Elektro Celje used the incentive from Article 135 of the act in the national project USE IT WISELY, which took place in 2021.

The incentive, which comes from Article 137 of the Act, is intended for the pilot billing of self-consumption with the electrical energy for users in the community. A community of end customers is defined as a community with one or more production devices from renewable energy sources, connected at low voltage to the same local transformer station, participating in a qualified project, it is possible to calculate the network fee based on the concept of locational netting of production and consumption of all users in the community with a billing interval of 1 hour. All collection and delivery points in the community must belong to the same responsible balance group.

The DSO determines the administrative measurement point, in which it determines the net received or transmitted energy of the community based on measurements at the collection and delivery points of all users in the community.

End users in the community are entitled to compensation for achieving self-sufficiency in the form of a reduction in network fees and it depends on the determined amount of energy of group self-sufficiency in the community within individual billing intervals. The energy of group self-sufficiency in the community is the amount of absorbed energy of all end customers in the community, which is fully covered in a single billing interval by the transmitted electricity produced in all production facilities from renewable energy sources in the community. The distribution operator determines the compensation for each interval by distributing group self-sufficiency energy among all end-users in the community in proportion to the share of energy received by each end-user and multiplying the obtained amounts by the valid tariff network item in the billing interval and a factor of 0.8.

The compensation from the previous paragraph is shown by the distribution operator on the account of the active customer in the form of a special separate item of network fee reduction for achieving self-sufficiency in the community.

The distribution operator must provide the end customer and the aggregator or other authorized person with effective access to information on the end customer's consumption, the proportional share of the amount of energy of group self-sufficiency, the total amount of energy produced and received in the community, and the net delivered or received energy at the level of the administrative measuring point of the community from of the second paragraph of this article. The DSO must provide the end user with access to the detailed calculation of the network fee in accordance with the law. Information must be organized and displayed in a transparent manner. The end customer must also have access to an itemized bill according to the normal system tariff monthly for comparison purposes. The DSO must provide the client with access to this data for the duration of the pilot project.

If the end user's energy supplier issues a joint invoice for energy supply and network use, the DSO must forward all the necessary data for billing and display of the item on the invoice from the previous paragraph to the competent supplier.

In the future in Slovenia, the dynamic tariffing of network charges for electricity will no longer be intended for pilot projects but will be part of regular legislation. For the purpose of promoting flexible use of the network in various closed geographical areas of the distribution system, the distribution operator determines dynamic tariff items for the network fee for the distribution system. The DSO will determine the local dynamic tariff in such a way that, based on the dynamic tariff items of the network charge for the distribution system for each closed geographical area, the user of the system will be encouraged to provide net benefits through adjusted use of the network.

The local dynamic tariff will primarily be aimed at reducing the consumption of system users at the time of critical peak load of the local network or increasing the consumption of system users at the time of critical net production of the local network with the aim of ensuring the greatest possible relief of the distribution system, reducing electricity losses or ensuring adequate voltage quality in the local network. The onset of dynamic tariff items for the network fee for the distribution system can be predicted in advance or in real time. The period of validity and the amount of dynamic tariff items will be determined by the DSO based on forecasting the operating state, considering environmental factors or the availability of energy from dispersed energy sources. The DSO will determine the dynamic tariff items of the network charge for the distribution system for working energy with the aim of encouraging the adaptation of the use of the network so that the aggregated tariff item of the network charge for energy is markedly increased or markedly reduced in each billing interval.

4.2.2 Slovenian pilot rewards in current tariff system

There are currently no dynamic tariffs available in the Slovenian pilot area, as far as the price aspect of electricity for household consumption is concerned. Electricity prices with a resolution of 1 hour are available on the https://www.bsp-southpool.com/day-ahead-trading-results-si.html website, namely for the intraday and day ahead market, but none of the electricity retailers offer such packages to the end customers. From this point of view, it is not possible to expect benefits from the dynamic electricity price tariffing in the Slovenian pilot area. On the basis of dynamic pricing the end users could adjust the consumption of electricity on an hourly basis which would be directly correlated with price aspect on bill at the end of the month.

Currently, in the abovementioned pilot area, it is possible to choose between a one-tariff and a two-tariff system for recording and price evaluation of consumed electricity. The single tariff system includes all business and household electricity consumers who have installed self-sufficient solar power plants and other electricity consumers who want to receive electricity at a single tariff within one day. In the two-tariff system, there are household and business customers who do not have a self-sufficient solar power plant installed and who want to receive electricity according to the two-tariff system (the lower tariff is the tariff that starts at 10:00 p.m. of the previous day and ends at 6:00 a.m. of the day, the higher tariff starts at 6:00 a.m. and ends at 10:00 p.m. within the same day). For end users who use one tariff system for recording the consumed electricity and have a self-sufficient solar power plant installed at the same time, it is optimal for the consumption inside the building to increase when the production from the self-sufficient solar power plant is the highest. In such a case, the end user is enabled not to take electricity from the network during periods of the day when he does not have his own production (period when electricity is more expensive), but instead has energy already prepared in the facility, which he can release in periods when needs (e.g. the produced electricity is stored with the help of a heat pump in a heat storage tank). In this case, the incentive for the end user is that electricity, which is cheaper, is primarily used.

On the other hand, the end user who uses two-tariff metering of consumed electricity is enabled to pre-prepare the facility during periods of lower tariffs (heat up the water inside the water storage boiler with heat pump) by releasing (heat up the building with pre stored hot water) stored electricity (stored inside hot water) into the facility itself during periods of higher tariffs. In this case, the incentive for the end user is the difference between the price of electricity in the higher tariff and the lower tariff. In the current situation, there is a 30% difference between the high and the low tariff for the electricity used in household consumption.

4.2.3 Personal, social and moral incentives

The Slovenian pilot has already identified a number of personal incentives (see below) that will be emphasised to potential and existing pilot participants and a forthcoming co-creation workshop will explore the types of and how social and moral incentives can be used to further support user engagement in DR.

Personal incentives cover both monetary and non-monetary rewards that, when presented to the customer, will motivate them to participate in DR. In the Slovenian pilot, getting free HEMS and sensors installed is a prerequisite for participating in DR events which will allow customers the opportunity to gain better insight into their energy consumption and potentially save money. For example, end user will be able to monitor the consumption of electricity in real time and, based on this, determine which device consumes the most (investment in more energy efficient devices). Visualising energy costs, energy consumption and current network grid status in the iFLEX Assistant App can make the consumer feel more in control, more efficient and smarter, thus also trigger non-monetary personal incentives. The planned co-creation workshop will explore what to visualise and how in order to support DR engagement.

Information material to support the recruitment of pilot participants will also highlight other benefits which support the personal incentive, e.g., that the network conditions for the distribution of electricity will improve for the end user (less grid voltage fluctuation), which for end users with a solar power plant means constant operation of the inverter at full power. The coefficient of self-consumption of the produced electricity from the solar power plant will thus increase for the end user. Another motivating factor is that the end user's equipment will operate in optimal weather conditions (improvement of coefficient of performance COP of heat pump).

As noted above, the forthcoming co-creation workshop with potential and existing pilot participants, will explore the value and meaning of exploiting social and moral incentives to get end users engaged (long-term) in DR. From a practical perspective, the workshop will discuss concrete ideas of how to implement and deploy such incentives so that they support and complement economic and personal incentives. Activating and tapping into social and moral incentives can be done in the iFLEX Assistant App itself and as such do not represent an explicit new service, product, or pricing model etc. (excluding DR and the iFLEX solution of course); rather by exploiting this type of incentives one reaches end users who are not wholly motivated by saving money. End user may of course still potentially save money because by participating in DR they may consume cheaper energy if not also less energy. Consequently, the DSO, energy provider etc. will also benefit as the end user participates in the DR events.

4.2.4 Flexibility measurement and verification

One key aspect of unlocking user participation in grid management via providing flexibility is having a solid Measurement and Verification plan, in order to calculate the amount of provided flexibility in response to Demand Response (DR) events. Within the context of the Slovenian pilot, implicit (i.e. tariff-based) and – possibly – explicit (i.e. incentive-based) DR will be tested. Hence, we need to separate the different cases of DR: explicit vs. implicit.

In explicit DR events, potential participants are requested to shift the consumption of certain flexible assets in a specific way. More detailed information on flexibility measurement and verification in the case of explicit DR is provided in the respective paragraph for the Greek pilot, namely Section 3.2.3. To be more precise on the Slovenian case, HVACs or heat pumps will constitute the main source of flexibility. Their metering data will be collected via the smart meters installed in the users' premises.

As regards implicit DR events, a different approach should be adopted due to their nature. To elaborate on this aspect, the potential participants in these programs are just informed about reduced tariffs in upcoming time periods and it is up to them to decide whether to adjust their electricity consumption. It is highlighted that potential participants are not requested to respond to the Aggregator. Hence, the proposed approach in order to calculate the harvested flexibility from the pilot users is to compare their total electricity consumption during the implicit DR event with their baseline consumption, as calculated by the Digital Twin Repository (DTR). Thus, the – positive or negative – difference of the actual consumption to the baseline can be calculated. Based on this approach, the iFLEX partners will be able to estimate the responsiveness of pilot users to implicit DR events. The dispatch of implicit DR events is expected to be investigated in the iFLEX project exclusively within the context of the Slovenian pilot.

5 Incentive mechanisms for the Finnish pilot

The flexibility in the Finnish pilot comes from the building's heating system, which is based on district heating, and especially from the thermal mass of the building that can be used to store energy. The occupants of the building have a lower limit for indoor temperature in their apartments, which provides the constraint for the flexibility management in the iFLEX Assistant. The indoor temperature lower limit in the apartments of the pilot building is set to 21 degrees Celsius and it has been agreed with the residents and specified in their rental contract. The same limit is used by the building management system operating the heating system. The flexibility management is based on the assumption that when the heating is turned off the heating energy stored in the building floors and walls can be utilized to provide flexibility before the indoor temperature drops below the limit (pre-heating is also possible to increase the indoor temperature and amount of heat stored into the building). The results obtained from the phase 1 of the pilots validate this assumption. The average amount of flexible capacity in the DR events was 195 kWh (divided between district heating and electricity). This was achieved with an average drop of 0.5 Celsius degree (the typical temperature during experiments was over 21.5 Celsius degree). If we would increase the variation to 1.0 Celsius degree (i.e., between 22.0 to 21.0 Celsius degree) the flexibility would increase to 390 kWh.

5.1 Modeling and analysis of economic incentive mechanisms

5.1.1 The Model

The building manager aims to acquire flexibility regarding district heating energy by turning on/off the heating, and obtain:

- value, by selling the flexibility (possibly through an aggregator) in the real-time wholesale/balancing market, and/or
- savings in the electricity bill (if any), in light of day-ahead hourly prices

Therefore, the net value (NV) of the flexibility equals: value plus savings, which should be always positive for building participation in flexibility management to be meaningful. The ultimate objective would be to maximize NV in the next 24h period, by turning on/off the heating for certain periods to be optimally selected, i.e., the start time and the duration of turning off the heating, also taking into account the following:

- internal temperature constraints
- external temperature forecast
- thermal model of the building, e.g., parameters κ,λ *(Li et al, 2011)*
- model of possible rebound effect (this is the extra energy to heat the building after the flexibility period again modeled based on building thermal parameters and forecast on outside temperature)
- flexibility value forecasts in the wholesale/balancing market
- building "participation constraint", namely that the total NV is at least 0 (obtained by doing nothing), or that the total NV exceeds a certain preset threshold to compensate for the costs of infrastructure and effort to apply the procedure. 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).

Our objective, for the time being, on behalf of the flexibility aggregator is to maximize flexibility (i.e., total energy savings) at a specific time slot of interest τ, while satisfying temperature constraints of the building occupants and not affecting user comfort at all or if affected (even insignificantly) to be properly compensated by means of incentives (not necessarily monetary).

We denote as $x^t_{n,0}$ the baseline energy consumption at time slot t, which consists of a portion for district heating $h^t_{n,0}$ and another portion for electricity consumption $w^t_{n,0}$. x^t_n, h^t_n, w^t_n denote the respective flexibility values offered by customer n. The building receives a monthly energy bill for the whole building which is apportioned to its residents. Let us assume c(xn) to be the energy bill for customer n. Note that while cutting off district heating energy corresponds to an equal reduction in heating energy consumed by each occupant n, their electricity consumptions may be different, while the occupants may also contradict the flexibility management mechanism by increasing their electricity consumption component of energy at the time slot of interest, e.g., by turning on electrical HVAC devices, the cooking oven, the electrical blankets and so on to compensate for the loss of heat. The occupants might also decrease their electricity consumption at the time slot of interest, e.g., by leaving the apartment.

We assume that the temperature drops with a linear model (Li et al, 2011), as described below:

$$T_n^{in}(t) = T_n^{in}(t-1) + \kappa(T_n^{out}(t-1) - T_n^{in}(t-1)) + \lambda x_n^t \tag{36}$$

Then, the aggregator's problem is to maximize energy flexibility at time slot *τ* as described below:

$$\textbf{Maximize:} \quad \sum_{n \in \mathcal{N}} x_n^{\tau} \tag{37}$$

$$\textbf{s.t.} \quad r x_n^{\tau} + U_n(x_{n,0}^{\tau} - x_n^{\tau}) - U_n(x_{n,0}^{\tau}) - c\left(\sum_{n \in \mathcal{N}} (x_{n,0}^{\tau} - x_n^{\tau})\right) + c\left(\sum_{n \in \mathcal{N}} x_{n,0}^{\tau}\right) \geq 0, \ \forall n \in \mathcal{N} \tag{38}$$

$$T_n^{min} \leq T_n^{in}(\tau) \leq T_n^{max}, \ \forall n \in \mathcal{N}, \tag{39}$$

$$\sum_{n \in \mathcal{N}} r x_n^{\tau} \leq B \tag{40}$$

r denotes the reward per unit of energy flexibility provided by the aggregator, *c*(.) is the billing function for energy consumption of occupant *n* and *B* denotes the budget limit of the flexibility provider to pay the rewards. The first constraint corresponds to *individual rationality* for each occupant n to participate in the flexibility management mechanism: the total reward for energy flexibility provided by the aggregator for each occupant *n* plus the energy bill savings should be greater or equal to the utility loss due to the offered flexibility of the occupant *n*. The second constraint aims to maintain the indoor temperature in each occupant's apartment within the constraints T_n^{min}, T_n^{max}, which can be also personalized. The third constraint in the optimization problem above corresponds to the budget limit of the aggregator for flexibility rewards.

The utility function *U*(.) is considered to be a concave continuously differentiable function of the indoor temperature, i.e., square root of the indoor temperature per time slot. The billing function can incorporate dynamic pricing, e.g., based on a dynamic tariff vector $\boldsymbol{\psi}$ for the different time slots of the day.

Note that the following facts hold true for the Finnish pilot:

- There is no electricity meter per apartment.
- Users have comfort constraints regarding temperature.
- Flexibility provided affects temperature.
- Users lose utility value (e.g., according to a concave function) from temperature drop.
- The bill for district heating is shared over all apartments and common space of the building.

5.1.2 Numerical Evaluation

We employed the REDD dataset (Kolter et al, 2011) regarding the baseline consumption of the users. This dataset contains detailed smart meter measurements and sensor readings with one-second time granularity for 6 houses. We aggregated the energy consumption in hourly slots and these are the baseline consumptions that we assumed in our evaluation, cf. Figure 20. The time slot of interest for aggregating flexibility is τ=13. First, we consider a "zero-discomfort and zero-incentives" version of the problem and maximize flexibility for the building manager, which can be extracted by each user without violating his individual temperature constraints. This corresponds to the problem (37) setting B=0 EUR in equation (40). The temperature constraints are set to be equal for all user: the minimum acceptable indoor temperature is assumed to be T_{min}=21 degrees Celsius and the maximum acceptable indoor temperature is assumed to be T_{max}=25 degrees Celsius. The indoor temperature at each apartment at the time slot of interest τ is assumed to be T_{in}=22 degrees Celsius, while the outdoor temperature is assumed to be T_{out}=2 degrees Celsius. The thermal parameters of the building are taken to be κ=0.03 (thermal insulation of the building), λ=4 (efficiency of the heating system of the building). First, we assume that there is no user discomfort associated to the indoor temperature drop as long as the indoor temperature remains within the desired bounds. Then, the flexibility obtained by each building is depicted in Figure 20.

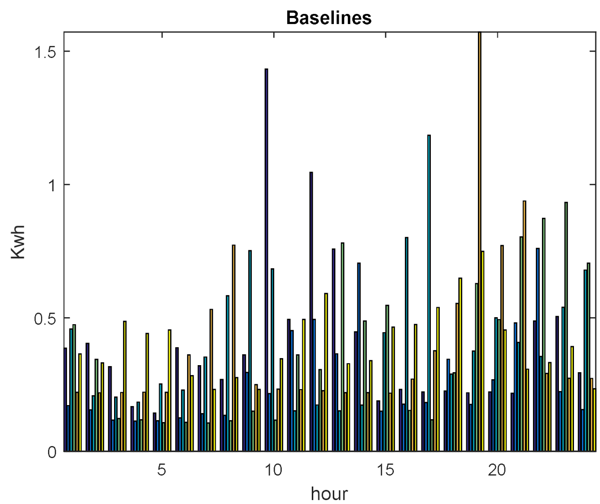


Figure 20: The baseline hourly energy consumption for 6 apartments.

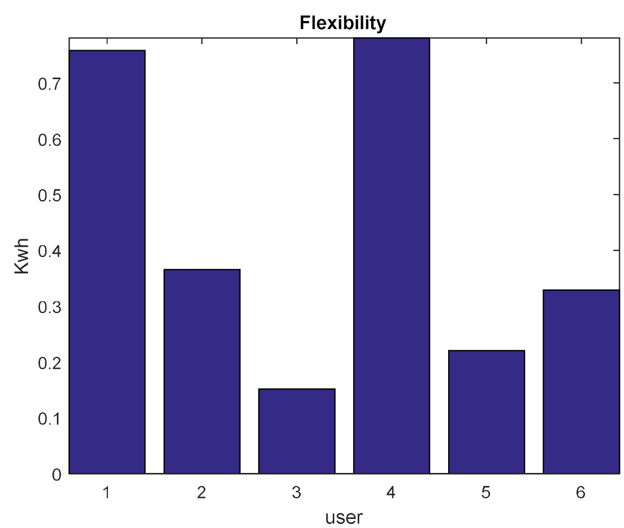


Figure 21: Flexibility given by users under no rewards, but incur no utility loss from indoor temperature drop within tolerable limits. B=0, T_{min}=20, T_{max}=25, T_{in}=22, T_{out}=2.

Then, we consider the case that there is utility loss (i.e., discomfort) associated with the indoor temperature drop for the occupants. Again, we assume no rewards. Then, the flexibility that can be obtained by the building manager is depicted in Figure 22. Evidently, it is individually rational for occupants to offer less flexibility in this case, as compared to the case of no discomfort associated with indoor temperature drop.

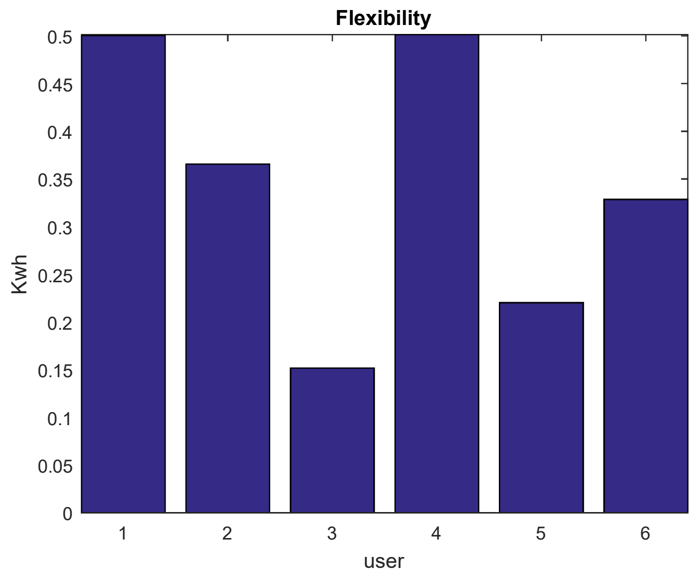


Figure 22: Flexibility given by users under no rewards that incur utility loss from indoor temperature drop within tolerable limits. B=0, T_{min}=20, T_{max}=25, T_{in}=22, T_{out}=2.

Subsequently, we consider the case that the building manager compensates users for their discomfort for indoor temperature drop and specifically we assume that *B*=10 EUR. Then, as depicted in Figure 23, the maximum flexibility that can be obtained by the flexibility manager rises up to the point of Figure 21. Therefore, rewards totally compensate users for their discomfort due to the flexibility obtained from them. The rewards given to each occupant are depicted in Figure 24.

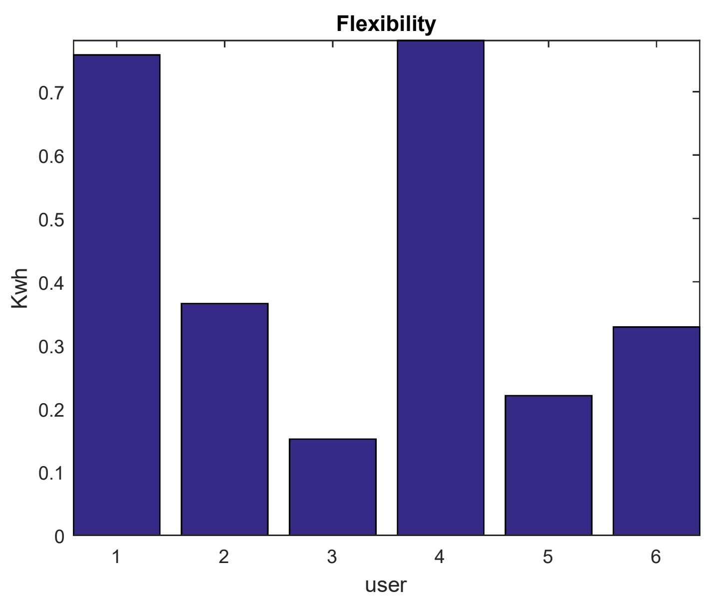


Figure 23: Flexibility given by users that incur utility loss from indoor temperature drop within tolerable limits and they are compensated with rewards. B=10, T_{min}=20, T_{max}=25, T_{in}=22, T_{out}=2.

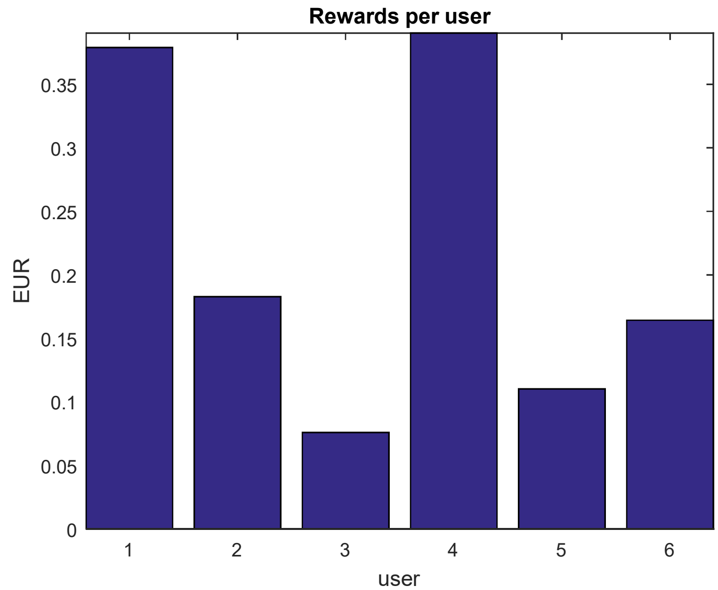


Figure 24: The rewards that compensate users for their flexibility when discomfort from indoor temperature drop is incurred to them.

Note that in case that no discomfort arises for building occupants from indoor temperature drop within the tolerable limits, there should be no need for compensating them with any rewards. We numerically evaluate this setting by assuming no utility loss from temperature drop for building occupants but non-zero available budget for user rewards, i.e., *B*=10 EUR. Then, as depicted in Figure 25.

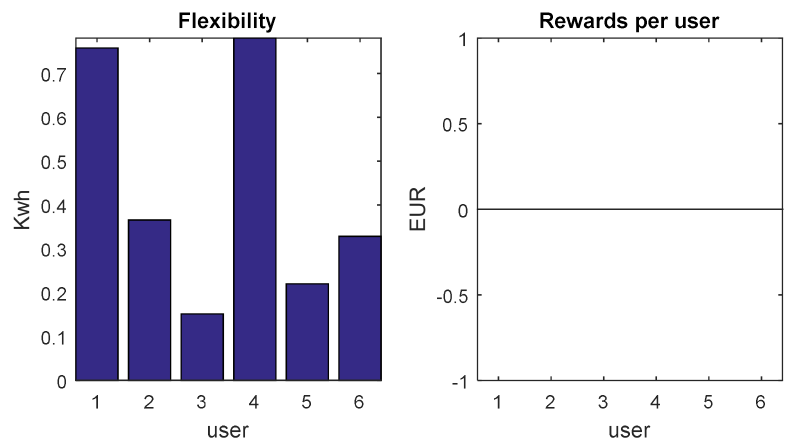


Figure 25: No rewards are needed for users for obtaining flexibility from them, when there is no utility loss associated to the flexibility exerted.

5.2 Practical issues for applying incentives

5.2.1 Incentives, Business, and Technical Issues

In the Finnish pilot the idea is to study iFLEX Assistants that operate HVAC system in a more intelligent way, improving energy efficiency and harnessing flexibility without the need to disturb the residents of the building. This means that the incentives should motivate the consumers to invest in iFLEX Assistant solutions that automate and personalize flexibility management. These incentives can be divided into the following three categories:

- ***Personal incentives***: Achieving optimal smart building operation, keeping the building's energy costs at a minimum and offering the flexibility for share any savings/bonuses attained by being flexible.
- ***Social incentives***: Actively contribute to a sustainable building energy consumption (being seen to do the right thing).
- ***Moral incentives***: Track the building's performance and progress (How am I / are we doing and am I / are we doing enough?).

While the absence of smart meters at the apartment level at the Finnish pilot contradicts our mathematical model, which assumes that the total energy consumption (i.e., electrical and heating) per building occupant can be measured, the model is still useful to investigate user incentives and behavior when such a flexibility management mechanism is employed in practical settings. For validating the findings of our model, individual smart meters are planned to be deployed in a handful of apartments in phase III of the pilot experiments.

In the Finnish pilot, the focus is on apartment building(s) with centralized HVAC system. This type of building forms a kind of energy community where the energy costs (and CO2 footprint) of the building are shared between residents (and the building owner). These types of buildings can be further classified into owner occupied flats and rental flats. With owner occupied flats the housing cooperative (formed by the flat residents/owners) makes the decision on investing iFLEX Assistant type of solutions. With rental flats the investment is made by the building owner. Therefore, the main incentives should be also targeted to them although residents also benefit indirectly through cheaper rents (residents could also priority the CO2 footprint of the building when selecting the flat to rent). The pilot building provides rental flats for students and is owned by an association called HOAS.

In practice this means that the iFLEX Assistant needs to be able to visualize the benefits for the building owner and residents. For the building owner these calculations are needed to demonstrate that they should invest in such technologies in other buildings as well. The results can be also used as a reference when targeting other building owners and housing cooperatives, as well as, to later validate that the promised benefits have been achieved with the investments. To this end, following visualizations are planned for the Finnish pilot: 1) reduction of energy costs (e.g., improved energy efficiency and implicit DR), 2) estimates on the revenue from explicit DR (i.e., participation through aggregation), and 3) estimates on CO2 reduction, and 4) estimates on flexibility available for RES integration and balancing.

There are many different products in the flexibility market. Some products are used for reserve (frequency regulation), such as Fast Frequency Regulation (FFR) (Fingrid, n.d.), Frequency Containment reserves, Normal or Disturbance (FCR-N or FCR-D) (Fingrid, n.d.), and Automatic Frequency Restoration Reserve (aFRR) (Fingrid, n.d.) in the Finnish flexibility market. These products are very critical for maintaining control and stability of the Nordic power system and therefore, there is a strict technical requirement and prequalification test for these products. Some other products are used for balancing; they are important for keeping the power system stable, but they are not as critical as reserve products. The providers usually have more time to react according to the Transmission system operator (TSO) request. As an example of balancing products, Manual Frequency Restoration Reserve (mFRR) can be named. There are other products that can be used for solving a local challenge, such as congestion in one distribution or transmission line.

The variety of flexibility products, the technical requirement and prequalification process, and also the minimum acceptable bid size in each market are some of the challenges for flexibility provision by small-sized customers. In addition, each country or system operator, including distribution and transmission system operators, may have its own technical requirements, which may be slightly different from the other one. Each of them may have its own platform working as a market operator and it makes it very difficult for the flexibility service providers (FSP) to integrate. There are other issues as well. For example, when there are no large harmonized markets, system operators cannot count certainly on the availability of flexibility resources at different times as a trustworthy solution; on the other hand, FSP cannot find a stable market with predictable prices for flexibility and would not invest on flexibility provision.

To solve some of these challenges in a systematic way, there are several research projects working on defining new holistic and harmonized solutions for flexibility market, for instance, the project defined under EU's eighth Framework Programme Horizon 2020 titled "*TSO – DSO Consumer: Large-scale demonstrations of innovative grid services through demand response, storage and small-scale (RES) generation*". Among them, the iFlex project collaborates with INTERRFACE and OneNet projects that create a cross-border, harmonized, and TSO & DSO coordinated market-based approach. The Market structure designed in OneNet aims to

- ***Seamless end-to-end process for market-based flexibility***: OneNet developed a harmonized and coordinated process for selecting and activating flexibility in multiple networks using real-time network states.
- ***Lower the entry barrier for flexibility by simplifying the process for flexibility service providers***: OneNet defined six general-purpose flexibility products; simplified and standardized prequalification, selection, and settlement processes.
- ***Ensure availability of short-term flexibility from multiple sources***: OneNet defined two new roles, Flexibility Register and TSO/DSO coordination to allow complex interactions between multiple resources, through multiple marketplaces, toward multiple networks, locally and across country borders.

More details on the collaboration between iFLEX and OneNet can be found in D8.1 of iFLEX.

By integrating the iFLEX concept with the OneNet market platform, some of the technical barriers to market integration of small-sized resources and providing monetary incentives for providers can be inherently mitigated. However, still, some challenges will remain.

As already mentioned, each flexibility product has technical requirements, a prequalification process, and a minimum acceptable bid size. In other words, an individual small-sized resource cannot participate in the market alone. There must be an aggregator that aggregates appropriate small-sized resources to create large enough and long enough bids for a specific market. Besides difficulties in finding the optimum market products for each resource, and optimum price for each aggregated bid, there are some other technical challenges that the iFLEX project is working on mitigating them.

Currently, in a normal situation, each customer is equipped with a smart meter that can measure the total consumption of a customer with a time resolution in the order of 1 h or 15 minutes. In these circumstances, FSP cannot measure the exact flexibility of each flexible resource separately. This type of measurement may not be enough for the prequalification process of critical products, such as FFR or FCR. To tackle this problem, the Finnish pilot building is equipped with a frequency meter that provides accurate enough measurements for the markets.

5.2.2 Baseline Calculation

In addition to load validation with measurements, there is a need to predict the baseline load of the consumer. The baseline is the normal consumption of a customer when there is no flexibility provision. In order to calculate the flexibility, the baseline needs to be calculated first. In large and industrial customers, the behavior is highly predictable. However, in a household customer, the behavior varies day by day. Therefore, calculating the baseline is not an easy way. Several studies work on baseline calculation for different products. They use the historical data for calculating the baseline. A methodology to calculate the baseline is the X of Y methodology: "The X of Y methodology involves averaging the level of demand/generation over X days in the last Y eligible days. The X days should be selected to best represent the event day (resource activation). A common variation of this method is the "High X of Y", which considers the X days with highest consumption in the Yday set. This is done for two reasons. Firstly, demand response programs will usually call for consumption reduction from consumers on days with very high consumption. Secondly, the High X of Y also minimizes the risk of unintended incentives that could result from underestimating the baseline." In the iFLEX project we address the baseline problem by forecasting the building baseline profile with an innovative approach that combines machine learning with physics-based modelling. By comparing the baseline forecast with the measurements outside of the DR events we can calculate the accuracy of the baseline estimation and take this into account in the flexibility offerings and compensation.

This deviation from the baseline is offered to the TSO reserve markets as flexible capacity. In household consumption, the amount of flexibility depends highly on the behaviour of the tenants. It makes it very difficult to predict the flexibility potential of a customer in advance, especially when there is no detailed measurement at the level of each resource. The lack of accurate estimation of flexibility in advance can highly reduce the monetary incentives in two ways: 1) If the aggregator cannot fulfil the bid, which is calculated according to the estimation, they need to pay a penalty, which usually is a couple of time larger than remuneration. 2) if the aggregator does not have long time accurate forecast, they cannot participate in capacity (availability market) which usually occurs a month to one year before the delivery time. To address this challenge the same hybrid modelling approach is utilized for forecasting the baseline consumption.

6 Conclusion

This deliverable has reported on the development, modelling, and assessment of economic incentive mechanisms for the three iFLEX pilots as carried out by Task 5.3 – *Incentive mechanisms and consumer engagement*, following submission of D5.2. In particular, a tailored approach was developed for each of the pilots due to their inherent differences. Therefore, appropriate individual models regarding the economic incentive mechanisms and their analysis are presented in this deliverable, together with the respective issues on the practical applicability of these mechanisms and with ideas for their combination with non-economic incentive mechanisms.

In particular, for the Greek pilot, an approach for the optimal management of the flexibility offered by residential users under uncertainty was developed; indeed, such uncertainty in the consumer response to the Demand Response (DR) signals may disrupt the goal of demand flexibility management. Therefore, a probabilistic user model to account for the uncertainty regarding whether a user will indeed achieve the flexibility specified (in conjunction with the incentives offered to this user) was developed, and subsequently introduced in the DR targeting process. Then, a suitable optimization framework to enable flexibility maximization and budget minimization was specified, comprising separate single-objective expressions with the appropriate constraints. Moreover, specific representative problems were defined and solved numerically for a wide range of user parameters, in order to illustrate the applicability and accuracy of the method, and to extract valuable insights. Also, techniques to resolve practical issues and to enable real-world implementation of the proposed scheme in the pilot sites were developed. Finally, practical issues on how to apply this approach in practice, and how to promote user engagement were defined, including the definition of appropriate lottery mechanisms motivated by prospect theory.

For the Slovenian pilot, an optimization framework that provides different forms of economic and non-economic incentives to prosumers with their own renewable resources (as opposed to simply consumers, which is the case with the other two pilots) was specified; this includes rewards, lotteries, peer-pressure, for providing flexibility at specific time slots. Dynamic tariffs per time slot for purchasing and selling electricity are accommodated in this framework as well. The overall problem is formulated as a Stackelberg game, played in turns by the aggregator and the users, and its analytical solution for simple cases of user utility functions is outlined for the case of full information by the aggregator concerning user-utility functions. Moreover, a distributed iterative algorithm is developed for solving the flexibility-management problem in the case where these functions are not known to the aggregator. Numerical results show that this optimization framework is capable to elicit the required flexibility from users at a minimum incentive cost, especially when monetary rewards are combined with peer pressure.

As for the Finnish pilot, the flexibility is taken to emerge from the building's heating system, and especially from the thermal mass of the building that can be used to store energy. Flexibility management is based on the assumption that when the heating is turned off the heat energy stored in the building can be utilized to provide flexibility before the indoor temperature drops below the contractually agree lower limit. Therefore, again an appropriate optimization problem was specified; namely, the objective is to maximize flexibility, while several factors are taken into account, such as internal temperature constraints, evolution of this temperature on the basis of external temperature forecast and thermal model of the building, and budget constraints incentives. Numerical results revealed that even when the internal temperature limit is not violated, the use of monetary incentive to compensate users for their discomfort leads to higher total flexibility. Issues on the practical implementation of the incentives' scheme considered, such as a method for calculating the baseline load, were also discussed.

As a final remark, it should be noted that the presented DR incentive mechanisms and schemes for the Greek pilots will be fine-tuned according to the insights that the project will gain from the analysis of users' responses to questionnaires (which is in progress) as well as from the interaction with user groups both in the workshops to be carried out with them and in the pilots themselves. These insights will also provide useful input for completing the modelling of combinations of monetary and non-monetary incentives.

7 List of figures and tables

7.1 Figures

7.2 Tables

8 References

(Minou et al, 2015) M. Minou, G. D. Stamoulis, G. Thanos and V. Chandan, “Incentives and targeting policies for automated demand response contracts,” IEEE SmartGridComm 2015.

(Hannah, 2015) L. Hannah. Stochastic optimization. International Encyclopedia of the Social & Behavioral Sciences, 2, 2015

(Kolter, 2011) J. Kolter and M. Johnson. REDD: A Public Data Set for Energy Disaggregation Research. Artif. Intell., 25, 2011.

(D5.2, 2021) iFLEX Consortium. Initial iFLEX consumer engagement and incentive mechanisms. Deliverable 5.2, 2021

(David, 2011) H. A. David, “Order statistics,” in International Encyclopedia of Statistical Science, M. Lovric, Ed. Springer Berlin Heidelberg, 2011, pp.1039–1040.

(Kahneman, 1979) D. Kahneman and A. Tversky, “Prospect Theory: An Analysis of Decision under Risk,” Econometrica, vol. 47, no. 2, pp. 263–291, March1979.

(Prelec, 1998) D. Prelec, “The probability weighting function,” Econometrica, vol. 66, no. 3, pp. 497–528, 1998.

(OGGG, 2015) Official Greek Government Gazette (2015). Decision 404, Serial Number 2773.

(Fingrid, n.d.) Fingrid. (n.d.). Fast Frequency Reserve. Retrieved September 20, 2022, from https://www.fingrid.fi/en/electricity-market/reserves_and_balancing/fast-frequency-reserve/

(Fingrid, n.d.) Fingrid. (n.d.). Frequency containment reserves (FCR-N, FCR-D up and FCR-D down), transactions in the hourly and yearly markets. Retrieved September 20, 2022, from https://www.fingrid.fi/en/electricity-market-information/reserve-market-information/frequency-controlled-disturbance-reserve/

(Fingrid, n.d.) Fingrid. (n.d.). Automatic frequency restoration reserve. Retrieved September 20, 2022, from https://www.fingrid.fi/en/electricity-market/reserves_and_balancing/automatic-frequency-restoration-reserve/

(Li et al, 2011) N. Li, L. Chen, and S. H. Low, “Optimal demand response based on utility maximization in power networks,” in IEEE Power and Energy Society General Meeting, 2011

(Kolter et al, 2011) J. Kolter and M. Johnson. REDD: A Public Data Set for Energy Disaggregation Research. Artif. Intell., 25, 2011.