Intelligent Assistants for Flexibility Management
(Grant Agreement No 957670)

D5.4. iFLEX consumer engagement and incentive mechanisms

Date: 2024-1-5

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: D5.4 Final iFLEX consumer engagement and incentive mechanisms v1.0.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	George D. Stamoulis, Thanasis Papaioannou, Christos Krasopoulos (AUEB)	2023-04-27	Initial table of contents
0.1	Kostas Kalogiannis (HERON), Malamatenia Patouni (HERON), Athanasios Papakonstantinou (HERON), Christos Simoglou (OPTIMUS), Stella Zacharia (OPTIMUS)	2023-06-21	Drafted section 4.2
0.2	Nikolaos Ntavarinos, Christos Krasopoulos (AUEB)	2023-07-30	Drafted sections 4.1, 4.3, 4.4, 4.5, 4.6
0.3	Christos Krasopoulos, Thanasis Papaioannou, George D. Stamoulis (AUEB)	2023-11-14	Drafted section 4.7, and chapters 5 and 6
0.4	Thanasis Papaioannou (AUEB)	2023-12-10	Drafted and finalized chapter 3
0.41	Christos Krasopoulos, Thanasis Papaioannou, George D. Stamoulis (AUEB)	2023-12-11	Drafted and finalized chapter 7 Finalized version for internal review
0.5	Antonis Dimakis, Mariza Tzouvali (AUEB)	2023-12-20	Additional internal reviews and suggestions for improvements
1	George D. Stamoulis, Thanasis Papaioannou, Christos Krasopoulos (AUEB)	2024-01-05	Deliverable finalization according to all suggestions and comments

Internal review history:

Reviewed by	Date	Summary of comments
Dusan Gabrijelcic (JSI)	20-12-2023	Accepted with minor comments
Igiso Zafeiratou (ICOM)	19-12-2023	Accepted with minor editorial improvements and comments

Index:

1. Executive summary

The purpose of this deliverable is to complete reporting on the work carried out by Task 5.3 – *Incentive mechanisms and consumer engagement*, and particularly by documenting the work accomplished by this Task, following the submission of D5.3. Within this period, T5.3 primarily focused on the development, modelling, and assessment of economic incentive mechanisms for the three iFLEX pilots. A tailored approach was developed and finalized for each one of the pilots, due to their inherent differences. To this end, 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 concrete propositions for their combination with non-economic incentive mechanisms.

In particular, for the Greek pilot, a mutually beneficial bilateral trading scheme is introduced between a RES and a DR aggregator. The objective of this scheme is to internally offset real-time energy imbalances before resorting to the flexibility market. It is considered that the DR aggregator manages the energy demand of users, and thus the actual provision of flexibility, subject to their offered monetary incentives and to their uncertainty in participating in DR events. It is taken that the RES aggregator faces penalties according to dual pricing for positive or negative imbalances. To this end, we develop an optimization framework to achieve the required flexibility, while addressing the trade-off between maximizing the profit of RES and DR aggregators and appropriately incentivizing the users. By using appropriate parameterization of the solution, the achievable revenue for the imbalance offsetting can be shared between the RES and the DR aggregators, while keeping users satisfied. Our analysis highlights the inter-dependencies of the demand-production energy imbalance to the user characteristics and the RES and DR aggregator profits. Based on our results, we show that a win-win outcome (for the RES and DR aggregators and the users) is possible for a wide range of cases, and we provide guidelines so that such bilateral agreements between RES and DR aggregators could emerge in practical settings. Furthermore, the integration of the incentives' component in the iFLEX assistant is presented. Also, various considerations for its effective implementation are discussed. These involve new studies on the discovery (i.e. learning) of the model of the users during the initial stage of the pilot. In that stage, incentives are provided using neither an optimization algorithm nor an explanation of the data exchanges between the incentives' component and the rest of the iFLEX assistant.

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 already specified and investigated in D5.3; this includes rewards, lotteries, and 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. Moreover, 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. Also, 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. In this deliverable, a complementary formulation was developed that includes optimal choice of flexibility at the level of individual appliance. This results in a suboptimal, yet privacy-friendly, approach; namely, to run first the distributed iterative algorithm between the aggregator and the users to estimate the total per user flexibility, and then to derive (for each user) the most proximal combination of flexible assets the user premises that can provide this flexibility.

As for the Finnish pilot, the building's heating system is taken to be the source of flexibility. In particular, flexibility emerges due to the thermal mass of the building, which can be used to store energy. Flexibility management is based on the following assumption: 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 agreed lower limit. Therefore, similarly as in the other pilots another optimization problem was already specified and investigated in D5.3; namely, the objective is to maximize the amount of flexibility, while several factors are taken into account, such as internal temperature constraints, evolution of the temperature on the basis of the external temperature forecast, the thermal model of the building, and budget constraints on the incentives. Numerical assessment of all models consistently confirmed that the flexibility aggregation can be effective, in the case where appropriate incentives are provided to the users, when the user-utility deterioration associated to drop of the indoor temperature in the apartments is considered and thus has to be compensated.

These investigations are complemented by the statistical analysis of the responses received to the user questionnaire, shedding light on users' main behavioral traits that can be combined with monetary incentives in order to enhance their effectiveness. One of the main lessons learned by this analysis is as follows: respondents believe that rewards and/or peer pressure can indeed motivate consumers to provide energy flexibility. Moreover, we found that consumers indeed have the ability to offer energy flexibility, as summarized by their knowledge and their capability, as well as that there is an opportunity dimension related to the user intentions to exert flexible energy behavior. This dimension involves the energy flexibility visualization, the automated energy flexibility or the energy flexibility advice and the external energy flexibility control, all of which are in-line with the iFLEX approach!

2. Introduction

The purpose of this deliverable is to complete reporting on the work carried out in Task 5.3 – *Incentive mechanisms and consumer engagement,* by documenting the work accomplished by this Task, following the submission of D5.3. Within this period, the Task 5.3 focuses primarily on the development, modelling, and assessment of economic incentive mechanisms for the three iFLEX pilots. A different approach was developed and finalized 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 concrete propositions are made for the combination of economic and non-economic incentive mechanisms.

The remainder of this deliverable is organized as follows: Chapter 3 contains the statistical analysis of the responses received to the user questionnaire, shedding light on users' main behavioral traits that can be combined with monetary incentives in order to enhance their effectiveness. Chapter 4 contains the final model of the incentive mechanisms for the Greek pilot, as well as a discussion on relevant practical issues. Chapter 5 contains the additional work on the model of the incentive mechanisms for the Slovenian pilot, the largest part of which was already presented in D5.3. Chapter 6 contains a new model of the incentive mechanisms for the Finnish pilot, based on a "public good" formulation; this chapter also includes numerical assessment of this model as well as of the incentives models in D5.3, and remarks on the cases where each of these models is applicable. Finally, Chapter 7 contains certain concluding remarks.

3. Statistical analysis of user questionnaires

3.1 Introduction and methodology

The iFLEX project has developed an on-line questionnaire to investigate the behavioral model of residential users towards providing energy flexibility based on DR signals. This questionnaire (presented in detail in the Appendix of D7.5) collected data on:

- user demographics and house appliances (Q1-Q10);
- gamification user types (Tondello et al., 2016); i.e.,
    - free spirit (Q12a),
    - socializer (Q12b),
    - socializer with some player elements (Q12c),
    - player (Q12d),
    - free spirit (Q12e),
    - philanthropist (Q12f),
    - achiever (Q12g),
- technology usage (Q13);
- user of energy consumption monitoring technology (Q14);
- motivation for providing flexibility;
    - environmental friendliness and sustainability (Q15a and Q15b),
    - economic rationality (Q15c and Q15d),
    - socializer (and normative social influence) (Q15e),
    - obedience (Q15f),
    - harm avoidance (Q15g),
- behavioral intentions to offer energy flexibility (Q16);
- energy awareness
    - selfish energy consumption (Q17a),
    - energy cost and consumption awareness (Q17b),
    - energy cost awareness (Q17d);
- flexibility awareness (Q17c);
- environmental personal norms;
    - importance of energy conservation (Q18a),
    - selfish energy consumption (Q18b),
- locus of control (Q19);
- personal disadvantages (Q20);
- external control for energy flexibility provision per appliance (Q21);
    - heat pump,
    - electric water heater,
    - electric or hybrid car,
    - A/C,
- preference for automated or manual flexibility provision (Q22);
- preferences for energy flexibility management; i.e.,
    - enable/disable automated management (Q23a),
    - hourly preferences on energy flexibility (Q23b),
    - energy advice to meet energy flexibility preferences (Q23c),
- energy flexibility visualization and communication preferences; i.e.,
    - energy monitoring (Q24a)
    - energy flexibility options view (Q24b)
    - energy flexibility results overview (Q24c)
    - energy flexibility notifications (Q24d).

The motivation- opportunity-ability (MOA) model of consumer behavior, shown in Figure 1, defines *three main factors that influence behavior: motivation, opportunity and ability*. To begin with **Motivation**, it is determined by the beliefs about and evaluation of outcomes of a behavior, which in turn influences the attitudes towards certain behavior and the intention to actually perform the behavior. In addition, the intention to perform certain behavior is influenced by social norms concerning the behavior. This social norm refers to the subjective norm of the theory of reasoned action, which is a person's perception of how others think one should or should not act (Ajzen & Fishbein, 1980). The factors ability and opportunity facilitate the step from intention to the actual performance of behavior. **Ability** to perform the behavior is based on knowledge about how to perform the behavior as well by habits which 'shortcut' the intentional process. **Opportunities** are contextual circumstances (external factors) that make performance of behavior convenient or can trigger certain behavior, for instance the placement of waste containers close to someone's home.

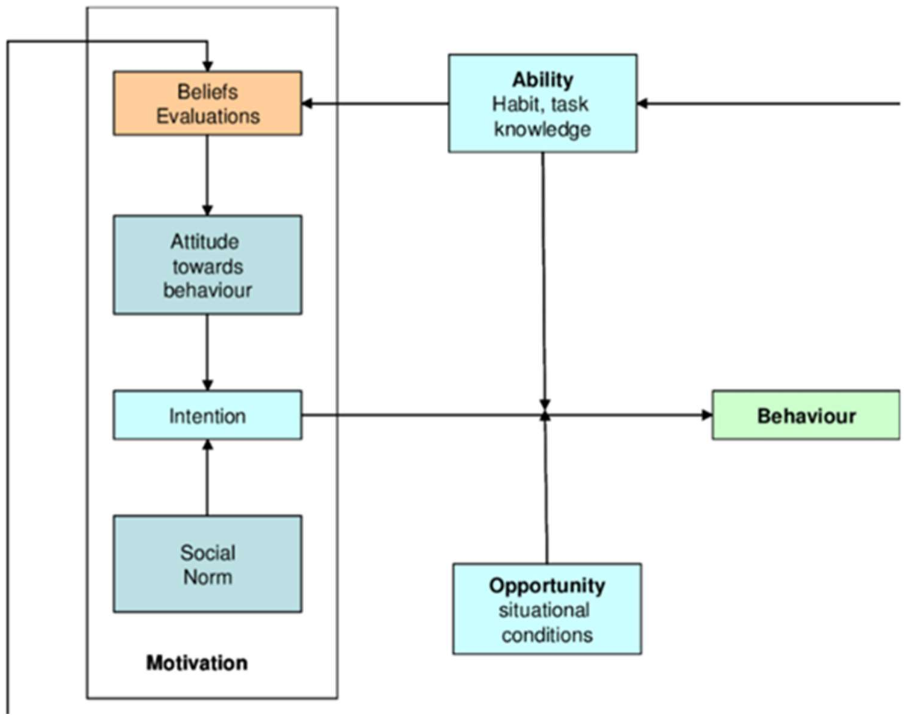


Figure 1: The Motivation-opportunity-ability (MOA) behavioral model.

We attempt to capture the behavioral intentions and their different motivational dimensions (i.e., motivation) to offer flexibility of residential users and corelate it with their flexibility capacity and their knowledge to do so (i.e. ability), and their situational conditions to do so (i.e. opportunity), and their preferences for external control and automation, while providing flexibility. The knowledge and problem awareness are an important psychological factor that affects energy-consumption behavior, while knowledge is part of the ability dimension in the MOA behavioral model. Attitude is part of the motivation dimension in the MOA behavioral model.

We also have questions that capture intrinsic motives, perceived personal responsibility and personal moral norms. This is also an important psychological factor that affects energy-consumption behavior. Moreover, personal responsibility is part of the perceived cost/benefit ratio (which is part of the motivation dimension in MOA model), which is another important psychological factor. Additionally, we collect information on the locus of control of residential users, as well as their desire for conformance to the social norms. The conformance to the social norms is also part of the motivation dimension in the MOA behavioral model. By assessing the predisposition of the participants to aid in energy conservation and sustainability, as well as their personal responsibility to this end, we will be in a position to better design flexibility management mechanisms towards empowering positive norms or modifying problematic ones.

We also record any personal disadvantages and the importance of personal comfort for residential users. Personal disadvantages are part of the perceived cost/benefit ratio that is an important psychological and motivational factor of energy-consumption behavior. Moreover, personal comfort is a factor of crucial importance for enabling energy-conserving behavior.

Also, according to the VBN norm theory (Stern et al., 1999), five individual-level variables impact environmentally significant behavior, namely individual personal values, environmental worldviews, awareness of adverse consequences of environmental problems, belief on self-efficacy to initiate action and individual personal norms. In VBN theory, these variables are causally related such that values and beliefs activate personal norms for pro-environmental behavior. However, it is also posited that variables earlier in the sequence can directly affect variables later in the sequence (i.e., direct and indirect effects). The beginning of the causal sequence is an individual's personal values. Values (e.g., altruism) orient an individual toward stewardship of others and his or her surroundings. An individual's belief about the environment is labelled environmental (or ecological) worldviews. The individual's awareness of the adverse consequences of environmental problems for valued objects results in assessing negative consequences for the valued object. Consequently, the individual assesses her/his ability to initiate action to alleviate these consequences. This may lead to activation of an individual's personal norms concerning pro-environmental behavior. To this end, we also assess influential factor for energy consumption behavior and flexibility, namely selfishness, socializing, environmental worldviews, self-reported flexibility intentions and personal norms on energy sustainability.

Also, according to (Frederiks, Stenner & Hobman, 2015) the psychological factors that mainly influence the energy consumption of residential users are:

- Knowledge and problem awareness. Understanding the multi-dimensional problem of energy sustainability and knowledge on how to conserve energy generally enable more sustainable energy-consumption behaviors. However, actually saving energy is most often influenced by other internal and situational factors. The absence of a direct link between knowledge and action is often referred to as “knowledge-action gap”.
- Attitude to environmental problems. Values reflect a global, abstract and relatively enduring set of beliefs, ideals and standards that serve as guiding principles in life (e.g., a person's general sense of right vs. wrong), whereas attitudes reflect more specific positive or negative evaluations of a particular idea, object, person, situation or activity. People with more positive attitudes are more likely to report engaging in environmentally responsible behavior than those with less positive attitudes. However, people typically make choices and behave in ways that minimize costs and maximise benefits to themselves (in terms of time, effort, money, comfort, etc.) rather than based on what is “best” for others and the environment (but, people are self-maximizing – value-action gap). Moreover, while attitudes may lead to positive intentions to save energy, various intervening factors (e.g., lack of knowledge about effective actions, social norms, perceived personal responsibility, self-efficacy, anticipated cost-benefit trade-offs, situational and institutional factors, etc.) may block this intention from being realised into actual behavior. Therefore, the link of attitude to pro-environmental behavior is characterized as loose, referred to as “value-action gap”.
- Intrinsic motives, perceived personal responsibility and personal moral norms. Intrinsic motives—that is, motivation that stems from personal interest, enjoyment or satisfaction in an activity itself, regardless of external pressures or rewards—have also been associated with pro-environmental behavior. (De Young, 2000) proposed four different intrinsic satisfactions and associated motives that may underpin environmental sustainability: satisfaction from striving for behavioral competence (e.g., enjoyment from solving problems and completing tasks); satisfaction from frugal, thoughtful consumption (e.g., enjoyment from survival based on careful management of finite resources); satisfaction from participating in the community (e.g., enjoyment from being involved in community activities); and satisfaction from luxuries (e.g., enjoyment from convenience and access to new/novel products). However, (Kollmuss & Agyeman, 2002) suggest that the larger primary motives that influence a wide range of behavior (i.e., altruistic and social values around living a pro-environmental lifestyle) are often surpassed or overridden by more immediate, selective motives (i.e., specific motives that influence particular actions and often evolve around one's own needs, such as being comfortable, saving money/time, reducing effort, etc.). It has been suggested that altruistic behavior is activated by personal norms, and acting in manner that is consistent with one's personal norms may lead to positive feelings of pride and self-satisfaction whereas acting in a manner inconsistent with personal norms may lead to negative feelings of guilt and regret. Pro-social behavior is influenced by moral or personal norms—i.e., feelings of strong moral obligation to perform certain types of pro-social behavior, including pro-environmental actions such as energy conservation (for reviews, see (Abrahamse & Steg, 2009), (Abrahamse & Steg, 2011) and (Bamberg & Möser, 2007). For personal norms to be activated, however, a person must first be aware that their behavior has an impact on others and/or

the environment (i.e., there must be awareness of consequences), and also feel a sense of personal responsibility for such impacts (i.e., termed "ascription of responsibility"). Perceived responsibility reflects the attribution of responsibility (i.e., self-blame, accountability, liability, obligation, etc.) for energy conservation to oneself rather than away from oneself to other people, the government, industry bodies, environmental groups, or other external entities. It is often argued that feeling personally responsible for environmental problems (e.g., accepting blame for ecological damage caused by excessive energy use) and for protecting the environment (e.g., feeling obligated to combat climate change by reducing carbon emissions) is positively associated with pro-environmental behavior. However, the strength of this relationship may be weak due to the same processes implicated in the aforementioned "value-action gap".

- Locus of control. Locus of control reflects a person's perception of whether they have the capability to enact change and/or control events that impact them. Individuals with a strong internal locus of control believe that they can exercise personal control over their own decisions, life circumstances and outcomes (i.e., belief that events arise primarily from internal factors, such as one's own motivation and actions), whereas those with a strong external locus of control believe that decisions, life circumstances and outcomes are controlled by environmental factors outside their influence (i.e., belief that events arise primarily from external factors, such as other people, the government, socio-economic influences, etc.).
- Perceived cost/benefit ratio. People are often motivated by self-interest and try to select alternatives that yield the highest benefit for the lowest cost—where "benefits" and "costs" may include ***scarce*** or valued resources such as time, effort, money, social status/acceptance, convenience, comfort, and so forth. Both economic and behavioral cost-benefit tradeoffs may influence pro-environmental behavior such as household energy consumption and conservation. Several categories of perceived advantages and disadvantages may be considered:
    - Personal disadvantages (e.g., beliefs regarding loss of comfort, coldness, unhealthiness, behavioral constraints, etc. imposed by an energy-saving lifestyle),
    - Societal advantages (e.g., beliefs regarding less environmental pollution, more energy for future generations, world energy supplies, etc.),
    - Personal responsibility (e.g., beliefs regarding a sense of duty/responsibility),
    - People short-sighted for immediate costs or benefits, but more farsighted for future ones. In daily life, there are countless situations where people procrastinate, postpone decisions, or delay actions because they are viewed as costly in the short-term, despite offering long-term benefits.
- Personal comfort. Personal comfort, particularly the perceived loss of comfort that any energy-saving measure might impose, may have a sizeable impact on household energy consumption. Any decrease in personal comfort, or perceived threat to lifestyle quality, may reduce the likelihood of engaging in conservation behavior.
- Normative social influence. It is well established that human beings make social comparisons, follow the behavior of other people, conform to social norms—i.e., the explicit and/or implicit rules, guidelines or behavioral expectations within a group or society that guide what is considered normal and/or desirable. Two distinct types of social influence can motivate human action to conform: injunctive norms, which raise a person's awareness of the attitudes and/or behavior that are typically approved or disapproved by a social group (i.e., what people should think or do); and descriptive norms, which raise a person's awareness of the attitudes and/or behavior that are typically adopted, supported or performed by a social group (i.e., what people actually think or do). Information transmitted via social diffusion is more likely to influence behavior because it tends to be more easily perceived, favourably evaluated, and better understood and remembered than information transmitted via traditional means of education, marketing and advertising. As such, interpersonal sources of information may be more influential than media appeals in eliciting and sustaining reductions in energy use.

3.2 Analysis of responses in Greece

In Greece, 86 responses in the questionnaire were received and analysed. Based on the outlined theories, the semantics of the various questions employed, and the data collected from the Greek respondents, we have grouped the questions into groups (and calculated composite scores for them) as follows:

- Flexibility Capacity (Q11) with unrelated complementary components
- Free spirit (Q12a, Q12e) with Cronbach's alpha score 0.33. It should be noted that Cronbach's alpha coefficient (Cheung & Yip, 2005) is used to estimate the internal consistency of a composite score of a group. Estimating the reliability requires estimating a diagonal matrix that represents the variances

of measurement error. Values of Cronbach's alpha score between 0 and 0.2 suggest less reliable, between 0.2 and 0.4 suggest rather reliable, between 0.4 and 0.6 suggest quite reliable, between 0.6 and 0.8 suggest reliable, and between 0.8 and 1 suggest very reliable internal consistency of a composite score.

- Socializer (Q12b, Q12c, Q15e) with Cronbach's alpha score 0.63
- Philanthropist and Achiever (Q12f, Q12g) with Cronbach's alpha 0.67
- Rationality (and Selfishness) (Q12c, Q12d, Q15c, Q15d) with Cronbach's alpha score 0.66
- Digital Tech Expertise (Q13) with Cronbach's alpha score 0.68
- Energy Monitoring (Q14) with unrelated complementary components
- Environmental Worldview (Q15a, Q15b) with Cronbach's alpha score 0.52
- Personal Norms (Q17a-inverted, Q18a) with Cronbach's alpha score 0.40
- Flexibility Behavioral Intentions (Q16, Q19c-inverted) with Cronbach's alpha score 0.70
- Energy Flexibility Awareness (Q17b, Q17c, Q17d) with Cronbach's alpha score 0.59
- External Locus of Control (Q18b, Q19a, Q19b) with Cronbach's alpha score 0.46
- Personal Disadvantages (and Comfort Constraints) (Q20a, Q20b, Q20c) with Cronbach's alpha score 0.57
- External Flexibility Control (Q21, Q22) with Cronbach's alpha score 0.83
- Automated Flexibility / Flexibility Advice (Q23) with Cronbach's alpha score 0.77
- Flexibility Visualization (Q24) with Cronbach's alpha score 0.81

The bivariate correlations (Pearson Correlation Coefficient (Pearson, 1895)) among the various group identified for the Greek respondents are depicted in Table 1.

Table 1: Greek Respondents - Bivariate correlations among all composite scores identified with exponent "a" meaning significant at 0.05 (with two-tailed test of significance).

Correlations

		Free Spirit	Socializer	Rationality	Energy Flexibility Awareness	Personal Disadvantages	Environmental Worldviews	Personal Norms	Locus of Control	Flexibility Behavioral Intentions	External Flexibility Control	Automated Flexibility / Flexibility Advice	Flexibility Visualization	Flexibility Capacity	Digital Tech Expertise	Energy Monitoring	Philanthropist and Achiever
Free Spirit	Pearson Correlation	1.000	.109	.122	.012	.174	-.049	.015	-.089	-.242[a]	-.005	-.043	-.099	.145	.044	.029	-.105
	Sig. (2-tailed)		.317	.262	.915	.110	.654	.888	.413	.025	.965	.694	.366	.183	.688	.789	.334
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Socializer	Pearson Correlation	.109	1.000	.687[a]	.239[a]	.228[a]	.194	.077	.168	.246[a]	.072	-.113	.283[a]	.002	.094	-.040	.159
	Sig. (2-tailed)	.317		.000	.027	.035	.074	.479	.121	.023	.511	.300	.008	.987	.387	.717	.144
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Rationality	Pearson Correlation	.122	.687[a]	1.000	.259[a]	.356[a]	.164	-.025	.073	.350[a]	.185	.103	.422[a]	.108	.085	-.036	-.005
	Sig. (2-tailed)	.262	.000		.016	.001	.130	.818	.506	.001	.089	.348	.000	.321	.435	.740	.966
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Energy Flexibility Awareness	Pearson Correlation	.012	.239[a]	.259[a]	1.000	-.065	.087	.064	.237[a]	.176	.135	.135	.297[a]	.213[a]	.316[a]	.266[a]	.115
	Sig. (2-tailed)	.915	.027	.016		.550	.427	.555	.028	.105	.214	.216	.005	.049	.003	.013	.292
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Personal Disadvantages	Pearson Correlation	.174	.228[a]	.356[a]	-.065	1.000	.042	-.090	-.037	-.031	-.104	-.004	.133	-.090	-.229[a]	-.184	.000
	Sig. (2-tailed)	.110	.035	.001	.550		.700	.412	.738	.774	.342	.971	.222	.411	.034	.089	.997
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Environmental Worldviews	Pearson Correlation	-.049	.194	.164	.087	.042	1.000	.324[a]	.345[a]	.428[a]	.318[a]	.122	.039	-.029	.022	.180	.277[a]
	Sig. (2-tailed)	.654	.074	.130	.427	.700		.002	.001	.000	.003	.264	.720	.789	.842	.097	.010
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Personal Norms	Pearson Correlation	.015	.077	-.025	.064	-.090	.324[a]	1.000	.520[a]	.395[a]	.277[a]	.084	-.188	-.279[a]	-.035	-.004	.257[a]
	Sig. (2-tailed)	.888	.479	.818	.555	.412	.002		.000	.000	.010	.439	.083	.009	.748	.974	.017
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Locus of Control	Pearson Correlation	-.089	.168	.073	.237[a]	-.037	.345[a]	.520[a]	1.000	.454[a]	.250[a]	.172	.015	-.022	.149	.242[a]	.302[a]
	Sig. (2-tailed)	.413	.121	.506	.028	.738	.001	.000		.000	.020	.112	.889	.841	.171	.025	.005
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86

Flexibility Behavioral Intentions	Pearson Correlation	-.242[a]	.246[a]	.350[a]	.176	-.031	.428[a]	.395[a]	.454[a]	1.000	.497[a]	.319[a]	.251[a]	-.121	.195	.252[a]	.256[a]
	Sig. (2-tailed)	.025	.023	.001	.105	.774	.000	.000	.000		.000	.003	.020	.266	.072	.019	.017
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
External Flexibility Control	Pearson Correlation	-.005	.072	.185	.135	-.104	.318[a]	.277[a]	.250[a]	.497[a]	1.000	.208	.111	-.020	.198	.230[a]	.116
	Sig. (2-tailed)	.965	.511	.089	.214	.342	.003	.010	.020	.000		.055	.310	.855	.067	.033	.288
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Automated Flexibility / Flexibility Advice	Pearson Correlation	-.043	-.113	.103	.135	-.004	.122	.084	.172	.319[a]	.208	1.000	.387[a]	-.001	.255[a]	.169	.073
	Sig. (2-tailed)	.694	.300	.348	.216	.971	.264	.439	.112	.003	.055		.000	.994	.018	.120	.505
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Flexibility Visualization	Pearson Correlation	-.099	.283[a]	.422[a]	.297[a]	.133	.039	-.188	.015	.251[a]	.111	.387[a]	1.000	.108	.281[a]	.147	-.044
	Sig. (2-tailed)	.366	.008	.000	.005	.222	.720	.083	.889	.020	.310	.000		.323	.009	.176	.689
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Flexibility Capacity	Pearson Correlation	.145	.002	.108	.213[a]	-.090	-.029	-.279[a]	-.022	-.121	-.020	-.001	.108	1.000	.115	.154	-.083
	Sig. (2-tailed)	.183	.987	.321	.049	.411	.789	.009	.841	.266	.855	.994	.323		.293	.158	.450
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Digital Tech Expertise	Pearson Correlation	.044	.094	.085	.316[a]	-.229[a]	.022	-.035	.149	.195	.198	.255[a]	.281[a]	.115	1.000	.468[a]	.113
	Sig. (2-tailed)	.688	.387	.435	.003	.034	.842	.748	.171	.072	.067	.018	.009	.293		.000	.300
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Energy Monitoring	Pearson Correlation	.029	-.040	-.036	.266[a]	-.184	.180	-.004	.242[a]	.252[a]	.230[a]	.169	.147	.154	.468[a]	1.000	.218[a]
	Sig. (2-tailed)	.789	.717	.740	.013	.089	.097	.974	.025	.019	.033	.120	.176	.158	.000		.044
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86
Philanthropist and Achiever	Pearson Correlation	-.105	.159	-.005	.115	.000	.277[a]	.257[a]	.302[a]	.256[a]	.116	.073	-.044	-.083	.113	.218[a]	1.000
	Sig. (2-tailed)	.334	.144	.966	.292	.997	.010	.017	.005	.017	.288	.505	.689	.450	.300	.044	
	N	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86	86

a. Significant at .05 level

We found that in the Greek pilot there is no relationship between personal disadvantages and flexibility behavior intentions. Moreover, we did not find any relation between flexibility capacity and flexibility behavior intentions.

3.3 Analysis of responses in Slovenia

For the case of Slovenia, 237 responses in the questionnaire were analysed. Based on the outlined theories above, the semantics of the various questions employed and the data collected from the all 237 respondents from Slovenia, we have grouped the various questions in the following groups (and calculated composite scores for them):

- Flexibility Capacity (Q11) with unrelated complementary components
- Free spirit (Q12a, Q12e) with Cronbach’s alpha score 0.05. This shows that for this dataset alone, this scale is less reliable.
- Socializer (Q12b, Q12c, Q15e) with Cronbach’s alpha score 0.48
- Philanthropist and Achiever (Q12f, Q12g) with Cronbach’s alpha 0.69
- Rationality (and Selfishness) (Q12c, Q12d, Q15c, Q15d) with Cronbach’s alpha score 0.73
- Digital Tech Expertise (Q13) with Cronbach’s alpha score 0.66
- Energy Monitoring (Q14) with unrelated complementary components
- Environmental Worldview (Q15a, Q15b) with reliability score (Cronbach’s alpha) 0.68
- Personal Norms (Q17a-inverted, Q18a) with Cronbach’s alpha score 0.20 (rather reliable)
- Flexibility Behavioral Intentions (Q16, Q19c-inverted) with Cronbach’s alpha score 0.72
- Energy Flexibility Awareness (Q17b, Q17c, Q17d) with Cronbach’s alpha score 0.59
- External Locus of Control (Q18b, Q19a, Q19b) with Cronbach’s alpha score 0.41
- Personal Disadvantages (and Comfort Constraints) (Q20a, Q20b, Q20c) with Cronbach’s alpha score 0.37
- External Flexibility Control (Q21, Q22) with Cronbach’s alpha score 0.77
- Automated Flexibility / Flexibility Advice (Q23) with Cronbach’s alpha score 0.80
- Flexibility Visualization (Q24) with Cronbach’s alpha score 0.67

The bivariate correlations (Pearson Correlation Coefficient) among the various group identified for the Slovenian respondents are depicted in Table 2.

Table 2: Slovenian Respondents - Bivariate correlations among all scales identified with exponent “a” meaning significant at 0.05 (with two-tailed test of significance).

Correlations

		Free Spirit	Socializer	Rationality	Energy Flexibility Awareness	Personal Disadvantages	Environmental Worldview	Personal Norms	Locus of Control	Flexibility Behavioral Intentions	External Flexibility Control	Automated Flexibility / Flexibility Advice	Flexibility Visualization	Flexibility Capacity	Digital Tech Expertise	Energy Monitoring	Philanthropist and Achiever
Free Spirit	Pearson Correlation	1.000	.072	.051	.144[a]	.006	-.030	-.081	-.037	.049	-.020	.021	.030	.140[a]	.103	.028	.037
	Sig. (2-tailed)		.272	.430	.026	.924	.650	.215	.575	.450	.755	.745	.649	.031	.112	.673	.575
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Socializer	Pearson Correlation	.072	1.000	.725[a]	.089	.019	.294[a]	.121	.284[a]	.410[a]	.046	.084	.112	.170[a]	.163[a]	.021	.365[a]
	Sig. (2-tailed)	.272		.000	.172	.772	.000	.064	.000	.000	.478	.199	.084	.009	.012	.743	.000
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Rationality	Pearson Correlation	.051	.725[a]	1.000	-.001	.074	.180[a]	.041	.205[a]	.319[a]	.018	.091	.149[a]	.121	.125	.043	.178[a]
	Sig. (2-tailed)	.430	.000		.983	.254	.005	.528	.002	.000	.788	.161	.022	.062	.055	.505	.006
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Energy Flexibility Awareness	Pearson Correlation	.144[a]	.089	-.001	1.000	-.085	.131[a]	.098	.179[a]	.265[a]	.179[a]	.333[a]	.229[a]	.191[a]	.167[a]	.208[a]	.185[a]
	Sig. (2-tailed)	.026	.172	.983		.193	.044	.134	.006	.000	.006	.000	.000	.003	.010	.001	.004
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Personal Disadvantages	Pearson Correlation	.006	.019	.074	-.085	1.000	-.009	-.160[a]	.005	-.078	-.006	-.071	.029	.029	-.030	-.029	-.112
	Sig. (2-tailed)	.924	.772	.254	.193		.886	.013	.945	.233	.922	.274	.661	.651	.649	.654	.085
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Environmental Worldview	Pearson Correlation	-.030	.294[a]	.180[a]	.131[a]	-.009	1.000	.357[a]	.419[a]	.391[a]	.039	.228[a]	.084	-.031	.021	-.019	.219[a]
	Sig. (2-tailed)	.650	.000	.005	.044	.886		.000	.000	.000	.547	.000	.200	.639	.746	.770	.001
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Personal Norms	Pearson Correlation	-.081	.121	.041	.098	-.160[a]	.357[a]	1.000	.319[a]	.355[a]	-.004	.147[a]	-.010	-.015	-.058	-.094	.189[a]
	Sig. (2-tailed)	.215	.064	.528	.134	.013	.000		.000	.000	.952	.024	.881	.812	.372	.148	.004
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Locus of Control	Pearson Correlation	-.037	.284[a]	.205[a]	.179[a]	.005	.419[a]	.319[a]	1.000	.464[a]	.143[a]	.195[a]	.174[a]	.043	.080	.011	.160[a]
	Sig. (2-tailed)	.575	.000	.002	.006	.945	.000	.000		.000	.028	.003	.007	.509	.218	.867	.014
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Flexibility Behavioral Intentions	Pearson Correlation	.049	.410[a]	.319[a]	.265[a]	-.078	.391[a]	.355[a]	.464[a]	1.000	.183[a]	.207[a]	.095	.080	.169[a]	.046	.319[a]
	Sig. (2-tailed)	.450	.000	.000	.000	.233	.000	.000	.000		.005	.001	.145	.218	.009	.483	.000
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
External Flexibility Control	Pearson Correlation	-.020	.046	.018	.179[a]	-.006	.039	-.004	.143[a]	.183[a]	1.000	.091	.089	.452[a]	.359[a]	.246[a]	.076
	Sig. (2-tailed)	.755	.478	.788	.006	.922	.547	.952	.028	.005		.161	.174	.000	.000	.000	.242
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Automated Flexibility / Flexibility Advice	Pearson Correlation	.021	.084	.091	.333[a]	-.071	.228[a]	.147[a]	.195[a]	.207[a]	.091	1.000	.482[a]	.087	.202[a]	.129[a]	.138[a]
	Sig. (2-tailed)	.745	.199	.161	.000	.274	.000	.024	.003	.001	.161		.000	.183	.002	.048	.033
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Flexibility Visualization	Pearson Correlation	.030	.112	.149[a]	.229[a]	.029	.084	-.010	.174[a]	.095	.089	.482[a]	1.000	.151[a]	.179[a]	.213[a]	.114
	Sig. (2-tailed)	.649	.084	.022	.000	.661	.200	.881	.007	.145	.174	.000		.020	.006	.001	.081
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Flexibility Capacity	Pearson Correlation	.140[a]	.170[a]	.121	.191[a]	.029	-.031	-.015	.043	.080	.452[a]	.087	.151[a]	1.000	.366[a]	.265[a]	.103
	Sig. (2-tailed)	.031	.009	.062	.003	.651	.639	.812	.509	.218	.000	.183	.020		.000	.000	.113
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Digital Tech Expertise	Pearson Correlation	.103	.163[a]	.125	.167[a]	-.030	.021	-.058	.080	.169[a]	.359[a]	.202[a]	.179[a]	.366[a]	1.000	.440[a]	.293[a]
	Sig. (2-tailed)	.112	.012	.055	.010	.649	.746	.372	.218	.009	.000	.002	.006	.000		.000	.000
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Energy Monitoring	Pearson Correlation	.028	.021	.043	.208[a]	-.029	-.019	-.094	.011	.046	.246[a]	.129[a]	.213[a]	.265[a]	.440[a]	1.000	.113
	Sig. (2-tailed)	.673	.743	.505	.001	.654	.770	.148	.867	.483	.000	.048	.001	.000	.000		.082
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237
Philanthropist and Achiever	Pearson Correlation	.037	.365[a]	.178[a]	.185[a]	-.112	.219[a]	.189[a]	.160[a]	.319[a]	.076	.138[a]	.114	.103	.293[a]	.113	1.000
	Sig. (2-tailed)	.575	.000	.006	.004	.085	.001	.004	.014	.000	.242	.033	.081	.113	.000	.082	
	N	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237	237

a. Significant at .05 level

3.4 Analysis of responses in Finland

For the case of Finland, 955 responses in the questionnaire were analysed. Based on the outlined theories above, the semantics of the various questions employed, and the data collected from the 955 respondents from Finland, we have grouped the various questions in the following groups (and calculated composite scores for them):

- Flexibility Capacity (Q11) with unrelated complementary components
- Free spirit (Q12a, Q12e) with Cronbach’s alpha score 0.19
- Socializer (Q12b, Q12c, Q15e) with Cronbach’s alpha score 0.48
- Philanthropist and Achiever (Q12f, Q12g) with Cronbach’s alpha 0.51
- Rationality (and Selfishness) (Q12c, Q12d, Q15c, Q15d) with Cronbach’s alpha score 0.77
- Digital Tech Expertise (Q13) with Cronbach’s alpha score 0.58
- Energy Monitoring (Q14) with unrelated complementary components

- Environmental Worldview (Q15a, Q15b) with reliability score (Cronbach's alpha) 0.59
- Personal Norms (Q17a-inverted, Q18a) with Cronbach's alpha score 0.45
- Flexibility Behavioral Intentions (Q16, Q19c-inverted) with Cronbach's alpha score 0.73
- Energy Flexibility Awareness (Q17b, Q17c, Q17d) with Cronbach's alpha score 0.55
- External Locus of Control (Q18b, Q19a, Q19b) with Cronbach's alpha score 0.5
- Personal Disadvantages (and Comfort Constraints) (Q20a, Q20b, Q20c) with Cronbach's alpha score 0.43
- External Flexibility Control (Q21, Q22) with Cronbach's alpha score 0.85
- Automated Flexibility / Flexibility Advice (Q23) with Cronbach's alpha score 0.82
- Flexibility Visualization (Q24) with Cronbach's alpha score 0.72

The bivariate correlations (Pearson Correlation Coefficient) among the various composite scores identified for the Finnish respondents are depicted in Table 3.

Table 3: Finnish Respondents - Bivariate correlations among all scales identified with exponent "a" meaning significant at 0.05 (with two-tailed test of significance).

Correlations

		Free Spirit	Socializer	Rationality	Energy Flexibility Awareness	Personal Disadvantages	Environmental Worldviews	Personal Norms	Locus of Control	Flexibility Behavioral Intentions	External Flexibility Control	Automated Flexibility / Flexibility Advice	Flexibility Visualization	Flexibility Capacity	Digital Tech Expertise	Energy Monitoring	Philanthropist and Achiever
Free Spirit	Pearson Correlation	1.000	-.060	-.003	.008	.106	-.022	-.089	-.125	-.159	-.024	.011	.022	.054	.083	.007	-.005
	Sig. (2-tailed)		.065	.929	.798	.001	.488	.006	.000	.000	.461	.730	.494	.094	.010	.837	.875
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Socializer	Pearson Correlation	-.060	1.000	.677	.022	.117	.366	.141	.329	.331	.164	.082	.230	-.051	.099	.043	.296
	Sig. (2-tailed)	.065		.000	.496	.000	.000	.000	.000	.000	.000	.011	.000	.114	.002	.187	.000
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Rationality	Pearson Correlation	-.003	.677	1.000	-.017	.195	.232	-.029	.166	.189	.111	.101	.249	-.056	.105	-.009	.132
	Sig. (2-tailed)	.929	.000		.598	.000	.000	.375	.000	.000	.001	.002	.000	.083	.001	.787	.000
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Energy Flexibility Awareness	Pearson Correlation	.008	.022	-.017	1.000	-.117	.037	-.059	.054	.054	.054	.023	.103	.253	.220	.332	.133
	Sig. (2-tailed)	.798	.496	.598		.000	.247	.069	.093	.093	.096	.469	.001	.000	.000	.000	.000
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Personal Disadvantages	Pearson Correlation	.106	.117	.195	-.117	1.000	-.008	-.070	-.043	-.053	.052	.054	.078	-.099	.052	-.082	.015
	Sig. (2-tailed)	.001	.000	.000	.000		.814	.030	.182	.099	.106	.095	.015	.002	.107	.012	.633
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Environmental Worldviews	Pearson Correlation	-.022	.366	.232	.037	-.008	1.000	.480	.442	.449	.187	.170	.205	.001	.095	.101	.221
	Sig. (2-tailed)	.488	.000	.000	.247	.814		.000	.000	.000	.000	.000	.000	.972	.003	.002	.000
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Personal Norms	Pearson Correlation	-.089	.141	-.029	-.059	-.070	.480	1.000	.506	.418	.117	.110	.083	-.094	-.028	-.053	.112
	Sig. (2-tailed)	.006	.000	.375	.069	.030	.000		.000	.000	.000	.001	.010	.004	.396	.104	.001
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Locus of Control	Pearson Correlation	-.125	.329	.166	.054	-.043	.442	.506	1.000	.514	.185	.136	.161	.022	.080	.057	.242
	Sig. (2-tailed)	.000	.000	.000	.093	.182	.000	.000		.000	.000	.000	.000	.501	.013	.081	.000
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Flexibility Behavioral Intentions	Pearson Correlation	-.159[a]	.331[a]	.189[a]	.054	-.053	.449[a]	.418[a]	.514[a]	1.000	.358[a]	.191[a]	.264[a]	.032	.143[a]	.116[a]	.251[a]
	Sig. (2-tailed)	.000	.000	.000	.093	.099	.000	.000	.000		.000	.000	.000	.324	.000	.000	.000
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
External Flexibility Control	Pearson Correlation	-.024	.164[a]	.111[a]	.054	.052	.187[a]	.117[a]	.185[a]	.358[a]	1.000	.173[a]	.152[a]	.148[a]	.187[a]	.135[a]	.101[a]
	Sig. (2-tailed)	.461	.000	.001	.096	.106	.000	.000	.000	.000		.000	.000	.000	.000	.000	.002
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Automated Flexibility / Flexibility Advice	Pearson Correlation	.011	.082[a]	.101[a]	.023	.054	.170[a]	.110[a]	.136[a]	.191[a]	.173[a]	1.000	.528[a]	.040	.151[a]	.133[a]	.143[a]
	Sig. (2-tailed)	.730	.011	.002	.469	.095	.000	.001	.000	.000	.000		.000	.213	.000	.000	.000
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Flexibility Visualization	Pearson Correlation	.022	.230[a]	.249[a]	.103[a]	.078[a]	.205[a]	.083[a]	.161[a]	.264[a]	.152[a]	.528[a]	1.000	.065[a]	.253[a]	.193[a]	.169[a]
	Sig. (2-tailed)	.494	.000	.000	.001	.015	.000	.010	.000	.000	.000	.000		.045	.000	.000	.000
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Flexibility Capacity	Pearson Correlation	.054	-.051	-.056	.253[a]	-.099[a]	.001	-.094[a]	.022	.032	.148[a]	.040	.065[a]	1.000	.231[a]	.328[a]	.010
	Sig. (2-tailed)	.094	.114	.083	.000	.002	.972	.004	.501	.324	.000	.213	.045		.000	.000	.759
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Digital Tech Expertise	Pearson Correlation	.083[a]	.099[a]	.105[a]	.220[a]	.052	.095[a]	-.028	.080[a]	.143[a]	.187[a]	.151[a]	.253[a]	.231[a]	1.000	.389[a]	.125[a]
	Sig. (2-tailed)	.010	.002	.001	.000	.107	.003	.396	.013	.000	.000	.000	.000	.000		.000	.000
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Energy Monitoring	Pearson Correlation	.007	.043	-.009	.332[a]	-.082[a]	.101[a]	-.053	.057	.116[a]	.135[a]	.133[a]	.193[a]	.328[a]	.389[a]	1.000	.129[a]
	Sig. (2-tailed)	.837	.187	.787	.000	.012	.002	.104	.081	.000	.000	.000	.000	.000	.000		.000
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955
Philanthropist and Achiever	Pearson Correlation	-.005	.296[a]	.132[a]	.133[a]	.015	.221[a]	.112[a]	.242[a]	.251[a]	.101[a]	.143[a]	.169[a]	.010	.125[a]	.129[a]	1.000
	Sig. (2-tailed)	.875	.000	.000	.000	.633	.000	.001	.000	.000	.002	.000	.000	.759	.000	.000	
	N	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955	955

a. Significant at .05 level

3.5 Collective analysis of all responses - Main lessons learned

Based on the outlined theories above, the semantics of the various questions employed and the data collected from the all 1278 respondents in the three pilot countries of iFLEX (Greece, Slovenia, Finland), we have grouped the various questions in the following groups (and calculated composite scores for them):

- Flexibility Capacity (Q11) with unrelated complementary components
- Free spirit (Q12a, Q12e) with Cronbach's alpha score 0.21 (rather reliable)
- Socializer (Q12b, Q12c, Q15e) with Cronbach's alpha score 0.46
- Philanthropist and Achiever (Q12f, Q12g) with Cronbach's alpha 0.57
- Rationality (and Selfishness) (Q12c, Q12d, Q15c, Q15d) with Cronbach's alpha score 0.77
- Digital Tech Expertise (Q13) with Cronbach's alpha score 0.61
- Energy Monitoring (Q14) with unrelated complementary components
- Environmental Worldview (Q15a, Q15b) with reliability score (Cronbach's alpha) 0.77
- Personal Norms (Q17a-inverted, Q18a) with Cronbach's alpha score 0.39
- Flexibility Behavioral Intentions (Q16, Q19c-inverted) with Cronbach's alpha score 0.72
- Energy Flexibility Awareness (Q17b, Q17c, Q17d) with Cronbach's alpha score 0.56
- External Locus of Control (Q18b, Q19a, Q19b) with Cronbach's alpha score 0.45
- Personal Disadvantages (and Comfort Constraints) (Q20a, Q20b, Q20c) with Cronbach's alpha score 0.42
- External Flexibility Control (Q21, Q22) with Cronbach's alpha score 0.84
- Automated Flexibility / Flexibility Advice (Q23) with Cronbach's alpha score 0.81
- Flexibility Visualization (Q24) with Cronbach's alpha score 0.73

Table 4: All Respondents – Significant bivariate correlations among all groups.

Correlations

		Free Spirit	Socializer	Rationality	Energy Flexibility Awareness	Personal Disadvantages	Environmental Worldviews	Personal Norms	Locus of Control	Flexibility Behavioral Intentions	External Flexibility Control	Automated Flexibility / Flexibility Advice	Flexibility Visualization	Flexibility Capacity	Digital Tech Expertise	Energy Monitoring	Philanthropist and Achiever
Free Spirit	Pearson Correlation	1.000	-.001	.027	.084[a]	.103[a]	.029	-.051	-.073[a]	-.097[a]	-.028	.036	.069[a]	.080[a]	.092[a]	.003	.066[a]
	Sig. (2-tailed)		.959	.336	.003	.000	.303	.068	.009	.001	.317	.198	.014	.004	.001	.909	.017
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Socializer	Pearson Correlation	-.001	1.000	.691[a]	.075[a]	.111[a]	.380[a]	.158[a]	.330[a]	.360[a]	.139[a]	.104[a]	.245[a]	-.002	.138[a]	.046	.336[a]
	Sig. (2-tailed)	.959		.000	.007	.000	.000	.000	.000	.000	.000	.000	.000	.947	.000	.097	.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Rationality	Pearson Correlation	.027	.691[a]	1.000	.010	.190[a]	.246[a]	.004	.174[a]	.229[a]	.107[a]	.110[a]	.250[a]	-.016	.136[a]	-.007	.176[a]
	Sig. (2-tailed)	.336	.000		.724	.000	.000	.879	.000	.000	.000	.000	.000	.562	.000	.806	.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Energy Flexibility Awareness	Pearson Correlation	.084[a]	.075[a]	.010	1.000	-.077[a]	.111[a]	-.001	.111[a]	.111[a]	.038	.102[a]	.181[a]	.241[a]	.213[a]	.292[a]	.187[a]
	Sig. (2-tailed)	.003	.007	.724		.006	.000	.963	.000	.000	.172	.000	.000	.000	.000	.000	.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Personal Disadvantages	Pearson Correlation	.103[a]	.111[a]	.190[a]	-.077[a]	1.000	.016	-.067[a]	-.021	-.053	.042	.049	.088[a]	-.062[a]	.039	-.072[a]	.020
	Sig. (2-tailed)	.000	.000	.000	.006		.564	.017	.455	.059	.134	.079	.002	.027	.160	.010	.467
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Environmental Worldviews	Pearson Correlation	.029	.380[a]	.246[a]	.111[a]	.016	1.000	.453[a]	.442[a]	.450[a]	.134[a]	.201[a]	.243[a]	.009	.092[a]	.084[a]	.272[a]
	Sig. (2-tailed)	.303	.000	.000	.000	.564		.000	.000	.000	.000	.000	.000	.736	.001	.003	.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Personal Norms	Pearson Correlation	-.051	.158[a]	.004	-.001	-.067[a]	.453[a]	1.000	.469[a]	.397[a]	.082[a]	.121[a]	.091[a]	-.074[a]	-.015	-.041	.138[a]
	Sig. (2-tailed)	.068	.000	.879	.963	.017	.000		.000	.000	.003	.000	.001	.008	.593	.141	.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Locus of Control	Pearson Correlation	-.073[a]	.330[a]	.174[a]	.111[a]	-.021	.442[a]	.469[a]	1.000	.498[a]	.149[a]	.160[a]	.194[a]	.034	.076[a]	.072[a]	.246[a]
	Sig. (2-tailed)	.009	.000	.000	.000	.455	.000	.000		.000	.000	.000	.000	.231	.007	.010	.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Flexibility Behavioral Intentions	Pearson Correlation	-.097[a]	.360[a]	.229[a]	.111[a]	-.053	.450[a]	.397[a]	.498[a]	1.000	.307[a]	.196[a]	.250[a]	.036	.165[a]	.116[a]	.281[a]
	Sig. (2-tailed)	.001	.000	.000	.000	.059	.000	.000	.000		.000	.000	.000	.201	.000	.000	.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
External Flexibility Control	Pearson Correlation	-.028	.139[a]	.107[a]	.038	.042	.134[a]	.082[a]	.149[a]	.307[a]	1.000	.138[a]	.108[a]	.194[a]	.210[a]	.137[a]	.079[a]
	Sig. (2-tailed)	.317	.000	.000	.172	.134	.000	.003	.000	.000		.000	.000	.000	.000	.000	.005
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Automated Flexibility / Flexibility Advice	Pearson Correlation	.036	.104[a]	.110[a]	.102[a]	.049	.201[a]	.121[a]	.160[a]	.196[a]	.138[a]	1.000	.538[a]	.059[a]	.168[a]	.134[a]	.153[a]
	Sig. (2-tailed)	.198	.000	.000	.000	.079	.000	.000	.000	.000	.000		.000	.035	.000	.000	.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Flexibility Visualization	Pearson Correlation	.069[a]	.245[a]	.250[a]	.181[a]	.088[a]	.243[a]	.091[a]	.194[a]	.250[a]	.108[a]	.538[a]	1.000	.094[a]	.251[a]	.201[a]	.195[a]
	Sig. (2-tailed)	.014	.000	.000	.000	.002	.000	.001	.000	.000	.000	.000		.001	.000	.000	.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Flexibility Capacity	Pearson Correlation	.080[a]	-.002	-.016	.241[a]	-.062[a]	.009	-.074[a]	.034	.036	.194[a]	.059[a]	.094[a]	1.000	.246[a]	.291[a]	.041
	Sig. (2-tailed)	.004	.947	.562	.000	.027	.736	.008	.231	.201	.000	.035	.001		.000	.000	.142
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Digital Tech Expertise	Pearson Correlation	.092[a]	.138[a]	.136[a]	.213[a]	.039	.092[a]	-.015	.076[a]	.165[a]	.210[a]	.168[a]	.251[a]	.246[a]	1.000	.393[a]	.173[a]
	Sig. (2-tailed)	.001	.000	.000	.000	.160	.001	.593	.007	.000	.000	.000	.000	.000		.000	.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Energy Monitoring	Pearson Correlation	.003	.046	-.007	.292[a]	-.072[a]	.084[a]	-.041	.072[a]	.116[a]	.137[a]	.134[a]	.201[a]	.291[a]	.393[a]	1.000	.118[a]
	Sig. (2-tailed)	.909	.097	.806	.000	.010	.003	.141	.010	.000	.000	.000	.000	.000	.000		.000
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278
Philanthropist and Achiever	Pearson Correlation	.066[a]	.336[a]	.176[a]	.187[a]	.020	.272[a]	.138[a]	.246[a]	.281[a]	.079[a]	.153[a]	.195[a]	.041	.173[a]	.118[a]	1.000
	Sig. (2-tailed)	.017	.000	.000	.000	.467	.000	.000	.000	.000	.005	.000	.000	.142	.000	.000	
	N	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278	1278

a. Significant at .05 level

Based on the bilateral correlations in Table 4, we can derive the behavioral model among the various factors that affect flexibility behavior, as depicted in Figure 2. Note that, for readability purposes, we annotate in this figure only the Pearson correlations with value above 0.2. Also, we map all factors in the overall MOA model to better understand their scope and relations. In compliance with the VBN model, Environmental Worldviews are significantly correlated with the Personal Norms (0.453), and Personal Norms are significantly correlated with the Flexibility Behavior Intentions (0.397). Moreover, Rationality and Social Norms are strongly correlated with Flexibility Behavior Intentions and among them.

This finding leads to one of the *main lessons* learned by this analysis, namely that respondents believe that rewards and/or peer pressure can motivate consumers to provide energy flexibility. Moreover, we found that consumers should have the ability to offer energy flexibility, as summarized by their knowledge (i.e., environmental worldviews, energy flexibility awareness, digital tech familiarity) and their capability (i.e., energy monitoring capacity, possession of flexible energy assets or potential to provide energy flexibility). We also found that there is an opportunity dimension related to the user intentions to exert flexible energy behavior. The opportunity dimension involves the energy flexibility visualization, the automated energy flexibility or the energy flexibility advice and the external energy flexibility control, all of which are in-line with the iFLEX approach!

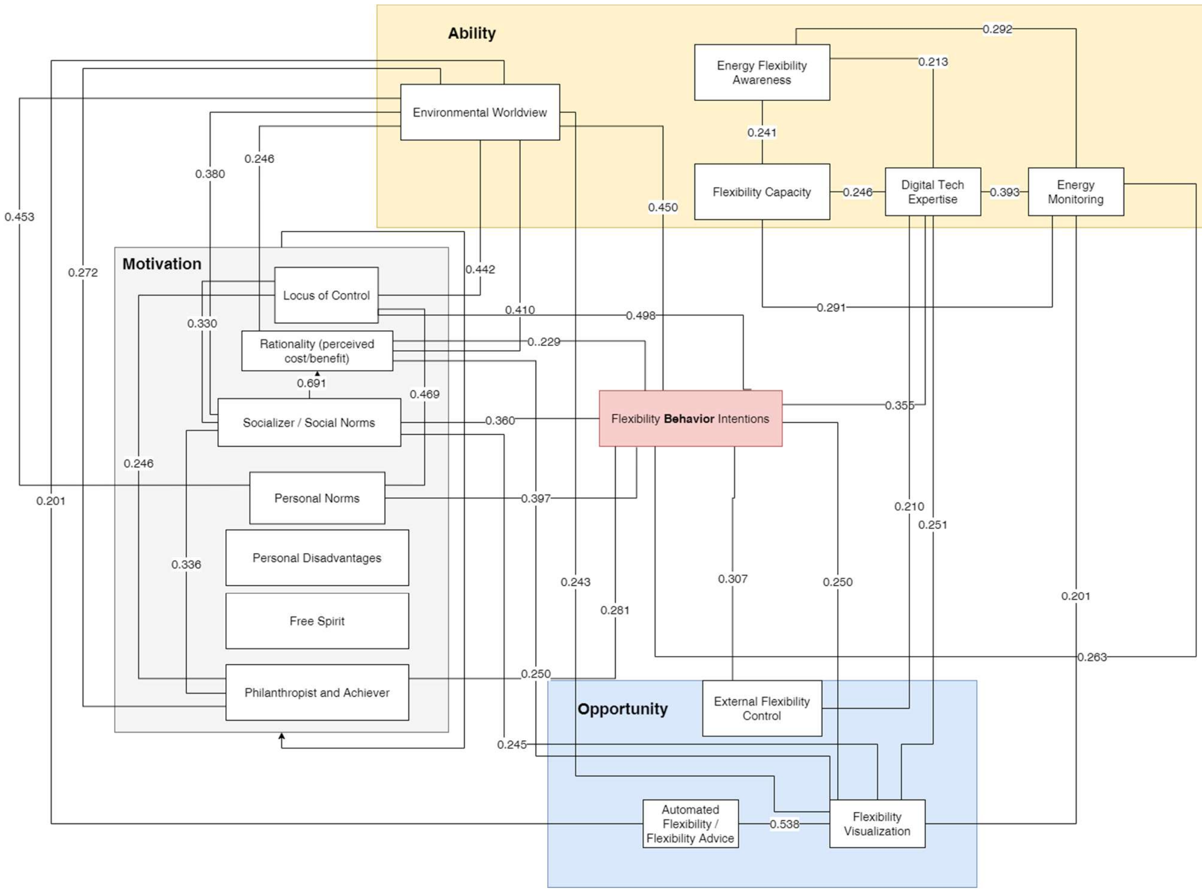


Figure 2: The overall behavioral model for residential users towards flexibility provision.

4. Provider business model, final model and Incentives Scheme for the Greek Pilot

4.1 Introduction

The integration of Renewable Energy Sources (RES) into the existing power grid has gained significant traction. Renewable generation, such as solar and wind, provides a cleaner and more environmentally-friendly alternative to conventional fossil fuel-based electricity production. However, the inherent intermittency and variability of these sources pose significant challenges to grid operators in maintaining a stable and reliable energy system. One of the key obstacles faced by RES aggregators is the management of imbalances caused by fluctuations in renewable energy generation. In order to address this issue and reduce revenue loss, a promising solution lies in the synergy between RES aggregators and Demand Response (DR) aggregators to offset any fluctuations in real-time generation by employing end-user Demand Side Flexibility (DSF) resources within the current structure of electricity markets.

Participation of DR Aggregators in electricity markets has gained significant attention as a means to address imbalances occurred from RES production and optimize their integration into the grid. In (Carreiro et al, 2017) the significance of the DR Aggregators' participation in electricity markets, as well as the importance of engaging end-users in implementing DR within a Smart Grid, are highlighted. Involving end-users manages intermittent RES energy production and enhances load-supply balance. The involvement of end-users in DR events has already been discussed in (Algarvio et al, 2023), where price-based demand response motivates consumers to adjust their energy consumption based on market prices or tariffs (active participation in electricity market).

Authors in (Mahmoudi et al, 2015) presented a novel approach for a market participant to handle its own production imbalances. Specifically, a wind producer is allowed to accomplish DR by creating numerous DR agreements with DR Aggregators, as a joint asset, in two stages; Day Ahead Market (DAM) clearing and regulated (balancing) market. At the first stage, the wind power producer submits its offers to DAM, considering the volume of fixed DR contracts which have been negotiated with the DR Aggregator. The second stage encompasses the final DR schedules and balancing settlements, through continuous run of a profit function, until all periods of the day are cleared.

Apart from the imbalances in generation, there is also a field of interest regarding the uncertainty in the receiving of DR resources. Part of the available literature proposes a dynamic reallocation of the consumption schedule, as in (Sharma et al, 2021), where uncertainties in real-time production are resolved via continuous refreshing of the load schedules in the environment of high PV penetration and load variability. Another approach on the subject is to quantify the possible variation in consumption. In (Yuan et al, 2023) a framework is suggested for energy management that includes a DR aggregator coordinating end-users. The uncertainty in terms of forecasting error in RES production is approximated by construction of a data-driven risk-adjusted uncertain set. Other methods prefer the adoption of robust optimization algorithms to account for this phenomenon. An optimization scheme with robustness capabilities is introduced in (Du et al, 2018) to create a schedule for devices operated manually to minimize the effect of the uncertainty of DR approval by the user.

A robust method is presented in (Paridari, 2016) for organizing the timing of smart appliances and electrical energy storages in households, with the goal of simultaneously decreasing the electricity expenses and CO_2 emissions. The suggested robust framework incorporates the uncertainty of user behavior, ensuring that the optimal schedule for appliances is less affected by unforeseen shifts in user preferences. Finally, in (Vahid et al, 2021) a hybrid stochastic-robust optimization approach is proposed to account for the uncertainties of the wholesale market prices and the participation rate of consumers.

In this chapter, we investigate a bilateral cooperation between RES and DR aggregators for mitigating imbalances in energy generation within an augmented common portfolio of RES units and end-user DSF resources, so that both of them achieve higher profits in relation to their direct and independent participation in the balancing market. We consider DSF uncertainty by appropriately adapting the user and the DR incentives model for the Greek pilot, thoroughly investigated in D5.3 of iFLEX and published in (Krasopoulos, Papaioannou & Stamoulis, 2022). This model includes: the probability of user participation according to the provided incentives, a user selection process that considers their positive attitude towards provision of flexibility and a healthy incentivization policy promoting fair remuneration for their services, under a suitable optimization framework combining those features. We also consider dual-tariff penalties for positive or negative imbalances and develop an optimization framework to achieve the required flexibility to offset imbalance, while addressing the trade-off among maximizing the profit of RES and DR aggregators and appropriately incentivizing the users. We numerically study our optimization framework and investigate the inter-dependencies of the demand-production energy imbalance to the user characteristics and the RES and DR aggregator profits. Our results indicate that mutually beneficial outcomes for the RES and DR aggregators and the users may emerge for a wide range of cases. Finally, we provide specific guidelines so that such bilateral agreements between RES and DR aggregators could emerge in real market settings.

The remainder of this chapter is as follows: In 4.2, the bilateral trading scheme is explained in detail, including the dual pricing scheme that provides fertile ground for this proposal. In 4.3, the model for providing incentives is then described both for the users – consumption side – and the revenue from the market – generation side. Afterwards, in 4.4, the optimization framework that realizes profit maximization for the stakeholders is exposed. In 4.5, a thorough analysis on the optimization results for a range of all the variables and parameters of the problem is conducted to investigate the dependencies among the three stakeholders. In 4.6, practical guidelines are provided to facilitate the efficient realization of such bilateral trading schemes that depend on user-side DR resources. In section 4.7 we have included considerations regarding the integration of the incentives component for the piloting phase of the project. Finally, in Section 4.8, we conclude our work.

4.2 Bilateral trading scheme

4.2.1 Cooperation of DR and RES Aggregators in electricity markets

Short-term electricity markets comprise a day-ahead market (DAM) and a balancing market (BM). Day-ahead market is a financial market where market participants (e.g. producers, retailers) sell and purchase electricity volumes at financially binding clearing prices (DAM clearing prices) for the 24 hours of the following day. On the contrary, the main purpose of the BM is the allocation of reserves capacity and the activation of upward/downward balancing energy in real-time (in the framework of the Real-Time Balancing Energy Market, RTBEM) provided by Balancing Service Providers (BSPs), such as thermal and hydro generating units, energy storage entities, etc., to fully address the positive/negative system imbalances in real-time, in order to maintain power system balance and ensure grid stability.

Non-dispatchable Renewable Energy Sources (RES) units (e.g. PV plants), due to their intermittent and stochastic nature, are one of the major sources of energy imbalances, which, in turn, require the provision of flexibility services from other eligible resources in real-time. In this context, end-user Demand Side Flexibility (DSF) resources, which are typically represented by a Demand Response (DR) Aggregator, can address and mitigate RES imbalances, before the RES Aggregator (market entity that represents, in general, small-scale RES units in the wholesale electricity market) seeks to perform balancing in the relevant RTBM. In practical terms, in case that the RES portfolio generates in real-time more than its declared DAM schedule, mainly due to inherent forecasting errors, the end-user DSF resources will be asked to increase their consumption accordingly, in order to collectively mitigate RES generation imbalances. Likewise, in case of less generation than the DAM schedule, DSF will be asked to decrease their consumption (D7.6, 2023).

4.2.2 Single and dual pricing scheme

There are two mechanisms depending on how the Balance Responsible Party's (BRP) behavior is preferred to be handled – the single-price and the dual-price model. Generally, the single pricing model is used when we want to incentivize the BRP (in our case the RES Aggregator) to reduce the aggravating imbalance. However, an imbalance with opposite direction that supports the system can be beneficial for the BRP. Under the single price settlement scheme not all the scenarios (i.e. system "short"- BRP "short", System "long"- BRP "short", System "short"- BRP "long", System "long"- BRP "long") create opportunities for the flexibility aggregator (in our case the DR Aggregator) to intervene and eventually reset the system's balance with the use of DR events. In the case where the RES Aggregator (who acts as the BRP) is in a so called "short" position and the real-time production lacks the energy declared on the DAM due to incorrect prediction, the RES Aggregator loses money, and its overall revenue is decreased. The decrement varies according to the deviation and the system's overall imbalance direction. In cases where the system's imbalance is "short" and the supply cannot cover the demand, the RES aggregator's revenue decrement will be higher as its position contributes to system's imbalance. On the other side, when the system is in a "long" position and the RES Aggregator is "short", RES's position assists the system to balance, hence the penalty for the deviation will be smaller. When the RES Aggregator is in a short position the DR Aggregator may intervene and cover fully the RES's short imbalances. When the RES Aggregator is long it gets paid by the TSO following the single-pricing scheme rules, thus there are no incentives for bilateral trade.

On the other hand, the main difference of the dual-pricing model compared to the single-price scheme is that for a given system's position the compensation price for deficit ("short") and surplus ("long") differ. The same price as in the single-pricing scheme can be used for the imbalance that deteriorates the system's position (RES "long" – system "long" or RES "short" – system "short") and the RES aggregator is expected to avoid the aggravating imbalance. For the imbalance that supports the system (RES "long" – system "short", RES "short" – system "long") the compensation price is designed in a way that it is not attractive to create imbalance to the supporting direction. This can be accomplished by selecting a neutral price which does not offer any significant profit but does not cause a revenue loss as well. The interesting fact about dual-pricing scheme is that opposed to single-price model the bilateral trading strategy can be applied in all possible real time scenarios.

More specifically, RES and DR Aggregators are considered to participate in a centralized wholesale electricity market where the dual-pricing scheme is adopted as regards the imbalance pricing, which is common in the European electricity markets (Nordic Model, 2019). Figure 3 illustrates the main characteristics of the "dual-pricing" scheme, as regards the imbalance pricing of market participants.

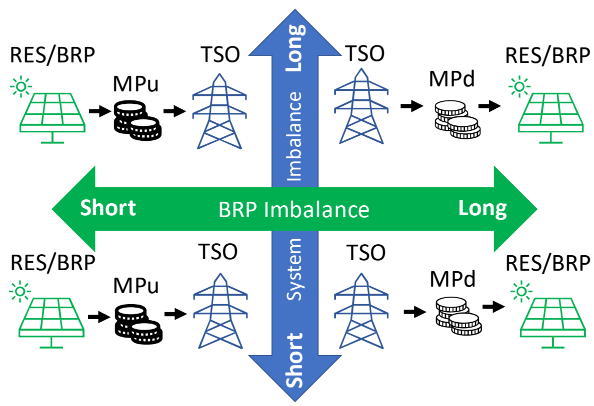


Figure 3: Dual pricing scheme

According to this pricing scheme, the remuneration/charge of a Balance Responsible Party (BRP) is independent of the direction of the system imbalance and only depends on its own imbalance direction. Specifically, in case that a BRP (e.g. RES Aggregator) is short (i.e. it produces in real-time less than its DAM schedule), it is charged for its production deficit by the Transmission System Operator (TSO) at 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 that a BRP is long (i.e. it produces in real-time more than its DAM schedule), for the excess generation it is remunerated by the TSO at 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-declare or under-declare its forecasted generation in the DAM. This, in turn, mitigates the possibility that gaming behaviors appear in the day-ahead and balancing market by all participants (BSPs and BRPs) (Nordic Model, 2019).

4.2.3 Bilateral agreement scheme

In the above context, it is considered that RES and DR Aggregators operate collectively under a common augmented portfolio of RES units and end-user DSF resources. For the financial clearing of the bilateral mitigation of the aforementioned RES generation imbalances, it is considered that a bilateral contract is concluded between the RES and DR Aggregators. The detailed terms of this bilateral contract can be decided mutually by the involved parties (DR and RES Aggregator), based on the following:

Let us assume that the bilateral contract price between RES and DR Aggregators is equal to $y_{D_{RES}}$ (in €/MWh), whereas $y_{D_{RES}}$ + *Premium* is defined as the settlement price between DR Aggregator and the end-users. $y_{D_{RES}}$+ *Premium* can be either lower or higher than $y_{D_{RES}}$, depending on the case (RES short or long, respectively, see explanation below). *Premium* is added to ensure that the end-user will benefit from its contribution either in case of RES short or long imbalances (see Figure 4).

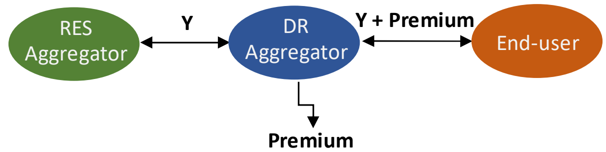


Figure 4: DR- RES Aggregators bilateral agreement scheme

Two distinct cases are identified, depending on the direction of RES imbalances (short or long), mathematically expressed as follows:

RES Short: $y_{D_{RES}} < (1-\delta) \cdot MP_u$ and $-\alpha \cdot y_{D_{RES}} < Premium < 0$ (1)

RES Long: $y_{D_{RES}} > (1+\delta) \cdot MP_d$ and $0 < Premium < P_{DA} - y_{D_{RES}}$ (2)

Where, $\delta \in (0,1)$ is a common parameter for both market cases, $\alpha \in (0,1)$ is a parameter that can be set arbitrarily and expresses the maximum DR Aggregator desired net profit (e.g. α=10%).
In case that RES Aggregator is short, DR Aggregator is remunerated by RES Aggregator at price $y_{D_{RES}}$. According to equation (1), $y_{D_{RES}}$ is lower than MPu, thus RES Aggregator is charged less for its generation deficit than it would be charged in case that it participated independently in the RTBM. On the other hand, DR Aggregator remunerates its customers for their decreased load at $y_{D_{RES}}$+ *Premium*, where Premium is negative and, therefore, DR Aggregator remunerates the end-user at a price lower than $y_{D_{RES}}$, thus retaining a profit equal to *Premium* for itself.

On the contrary, in case that RES Aggregator is long, RES Aggregator is remunerated by DR Aggregator at $y_{D_{RES}}$, which is higher than MPd, based on equation (2). $y_{D_{RES}}$+ *Premium*, where *Premium* is now positive, is the price that is charged by the DR Aggregator to the end-user for its increased consumption (i.e. end-user increases its consumption to counterbalance RES increased generation in real-time) and, therefore, the DR Aggregator retains again a profit equal to *Premium* for itself. However, the total price $y_{D_{RES}}$+ *Premium* that is charged to the end-user should be lower than the DAM price (as enforced by the right part of (2)) in order to properly incentivize them for their engagement (D7.6, 2023).

4.3 DR incentives modelling

4.3.1 Bilateral trading revenue model

The provision of incentives in this work is carried out according to the model proposed in (Krasopoulos, Papaioannou & Stamoulis, 2022) (with certain adaptations dictated by the dual pricing scheme) and more thoroughly explained in (D5.3, 2022). Our focus is on a provider/aggregator that aims to engage users in demand response (DR) and provides incentives to do so. We employ a model that addresses the uncertainty, regarding whether each targeted user will be able to achieve the desired flexibility. This model specifically relates to the selection of DR incentives to encourage users to abstain from using specific electrical devices. Participation in the DR event is realized by accepting the offered incentives and granting the provider control over the corresponding loads.

In our analysis, we consider a Renewable Energy Sources (RES) Aggregator to be playing the role of the BRP. End-User Demand Side Flexibility (EDF) resources can be employed with the purpose to mitigate RES imbalances before the RES Aggregator seeks to perform balancing in the relevant markets. The End-User resources are represented by a DR Aggregator who is responsible for informing the consumers about the upcoming DR event and the relevant adjustment they should perform on the flexible loads in their households. Following this strategy, the RES Aggregator achieves a reduction on the penalty caused by its imbalance, the End-User receives monetary rewards for helping the system to balance by activating or deactivating loads and the DR Aggregator receives a profit for his bilateral role.

RES Aggregator's payment from the Energy Market is the sum of the agreement made on the Day Ahead Market and the compensation for the Real Time production. As expected, it is quite unlikely that these two coincide. The stochastic nature of the second term in the right-hand-side of equation (3) affects the final revenue for the RES Aggregator.

$$Revenue_{RES} = MS_{RES} \cdot P_{DAM} + D_{RES} \cdot MP_u \quad \text{or} \quad Revenue_{RES} = MS_{RES} \cdot P_{DAM} + D_{RES} \cdot MP_d, \tag{3}$$

where MS_{RES} is the energy declared on the DAM and P_{DAM} the clearing price. D_{RES} represents the imbalance energy of the RES Aggregator, in other words the deviation between the real-time production and the production declared in the Day Ahead Market. MP_u, MP_d refer to imbalance prices and spreads evenly (usually ±20% hedge) around the P_{DAM} signifying that $MP_d = 0.8 \cdot P_{DAM}$ and $MP_u = 1.2 \cdot P_{DAM}$. MP_d indicates the marginal price of all accepted downward offers, and MP_u the marginal price of all accepted upward offers.

In our analysis the scenario where the RES Aggregator is short, under the dual-pricing scheme, has been examined. Equation (4) describes the revenue of RES after the intervention of the DR Aggregator:

$$New\_Revenue_{RES} = MS_{RES} \cdot P_{DAM} + D_{RES} \cdot y_{D_{RES}} \tag{4}$$

Depending on the DR Aggregator's approach and the value of $y_{D_{RES}}$, the RES revenue will vary accordingly. It is noted that D_{RES} takes negative values when RES is "short". Equation (4) is depicted on Figure 5 and it is plotted against two other scenarios - the former where RES has zero deviation and the latter where the RES's revenue is expressed according to Equation (3). From the RES's side it is preferable to agree on a $y_{D_{RES}}$ as close to 0 as possible but that would be very restrictive for the DR Aggregator since the available budget to be handled and distributed to the End-Users is heavily depended on $y_{D_{RES}}$. If the RES agrees on high $y_{D_{RES}}$ values the available budget increases as well and this gives the option to the DR Aggregator to target more consumers and offer them incentives to participate in the relevant DR event.

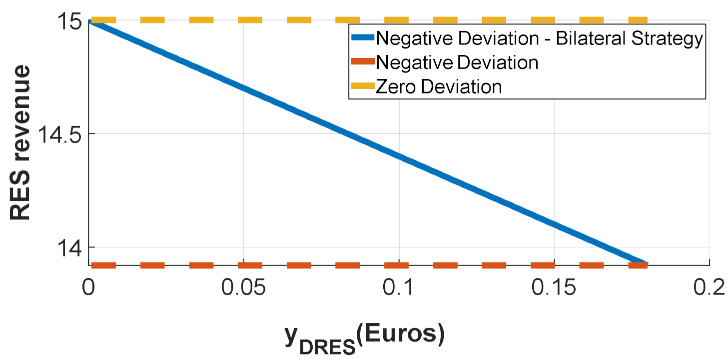


Figure 5: RES Revenue under different deviation scenarios

4.3.2 User modelling

The user here is presented with two options: either accepting the provided incentives r_n and actively contributing to the desired demand flexibility x_n, or rejecting the incentives and maintaining their regular consumption schedule. If the DR incentives adequately compensate the user's discomfort (Minou et al, 2011), which arises from refraining from using specific loads, taking into account the potential savings in the energy bill or other type of incentives, then participation in the DR event becomes the optimal decision for the user. In other words, if $r_n \geq NBloss(n)$ (representing the loss of Net Benefit due to DR), the user should participate. Consequently, the probability $p_n(r_n)$ for user n to participate in the DR event is defined as a step function rising from 0 to 1 at $r_n = r_{\min(n)}$. To incorporate this uncertainty into our analysis, a Bernoulli trial with a success probability $p_n(r_n)$ has been used. The probability function varies according to the economic incentives offered to the user n. In case of failure in this trial we assume that the user n does not take part in the DR event hence no flexibility is provided from the corresponding household. The incorporated uncertainty expressed by $p_n(r_n)$ (Equation (5)) for a user n with minimum acceptable incentives $r_{\min(n)}$ is a smooth approximation of the step function. Employing such a function rather than the unit-step function 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).

$$p_n(r_n) = \frac{1}{1 + e^{-a_n(r_n - r_{\min,n})}} \tag{5}$$

The above is a slightly modified version of the sigmoid function where $p_j(\mathrm{r_{min\,(n)}})$ equals 1/2 regardless of the value of a_n, which determines the steepness of the function. A larger value of a_n results in steeper rise of the function. Figure 6 provides a visual representation of the function's shape for different values of a_n and r_{min}.

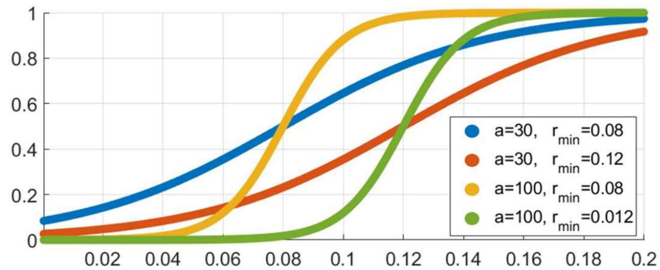


Figure 6: RES Revenue under different deviation scenarios

4.4 Optimization framework

The optimization problem of the DR Aggregator can now be specified. One of the main differences between this approach and the one presented in D5.3 is that the available budget for the DR Aggregator now is based on RES Aggregator's energy deviation D_{RES}. The impact that D_{RES} has on the model's results needs to be considered and for this reason scenarios for various values of D_{RES} will be examined through our optimization algorithm. Generally, it is expected that the worse the prediction of the RES Aggregator in the DAM, the more "space" is created for the DR Aggregator to fix the imbalance, hence the more budget will be available. The optimization process for the Flexibility Aggregator is to maximize its profit by using the available budget. If we assume that our case is based on the System "short" – RES "short" scenario, the optimization algorithm under the bilateral trading scheme can be expressed as follows:

$$\max\ \{ \mathrm{y_{D_{RES}}} \cdot \mathrm{D_{RES}} - \textstyle\sum_n [y_n \cdot r_n \cdot p_n(r_n)] \}$$

$$\text{s.t.} \begin{cases} DR_{profit} > 0 \\ RES_{profit} > 0 \\ r > r_{min} \\ X = D_{RES} \\ y_n \in \{0,1\} \end{cases} \Rightarrow \tag{6}$$

$$\Rightarrow \begin{cases} \Sigma_n [y_n \cdot r_n \cdot p_n(r_n)] < y_{D_{RES}} \cdot D_{RES} \\ D_{RES} \cdot (MPu - y_{D_{RES}}) > 0 \\ r > r_{min} \\ \Sigma_n [y_n \cdot x_n \cdot p_n(r_n)] = D_{RES} \\ y_n \in \{0,1\} \end{cases}$$

where $y_{D_{RES}}$ is the monetary compensation agreed between the RES and the DR Aggregator and for this model its value varies from 0…*MPu*. Through the offered compensation value of $y_{D_{RES}}$ the RES Aggregator can decrease its revenue loss which is caused by its deviation. Variable y_n varies for n = 1, … ,N and constitutes a binary decision variable for targeting user n, while r_n are the incentives offered to the user. We assume that a user n that is not targeted (i.e., if $y_n = 0$) is offered no incentives (i.e., $r_n = 0$).

The constraints of the optimization problem mainly ensure that the variables representing the profits for the DR and the RES Aggregator respectively take only positive values. For the former this is a net profit increase but for the latter this is not actually a profit, but rather a decrease of its revenue loss. Part of developing a fair optimization process is the fact that the targeted users are offered monetary incentives higher than the corresponding r_{min} even though it is expected that in some cases users might accept incentives somewhat smaller than r_{min}. Another constraint refers to the variable X which expresses the total flexibility. It is assumed that the deviation caused by the RES Aggregator needs to be covered fully by DR events.

The optimization framework determines the optimum way to cover this deviation - whether it is favorable to offer high r_n to a small number of users N or to offer lower r_n to a higher number of End-Users. We expect that the results will clarify how the conflicting profit variables of the participating entities are affected by D_{RES} and $y_{D_{RES}}$. An interesting point for further analysis would be the correlation of RES_{profit} with D_{RES} as this might reveal an interesting aspect that could potentially affect RES Aggregator's strategy. The distribution of the available budget among the interested parties will be part of the post analysis.

4.5 Analysis

In this section we investigate the relation between the DR budget created due to RES imbalances and the DR efficiency according to the user characteristics, using the optimization framework for the incentives model. The optimization will be executed for a range of values of the problem variables and user parameters (Table 1). The results shall shed light on how the DR and RES Aggregator and end-user profits are affected by the examined variables of D_{RES} and $y_{D_{RES}}$.

Table 5: Problem, market and user variables and parameters

Parameter	Min. val.	Max. val.	Variable	Min. val.	Max. val.
P_{DAM} (€)	0.15		D_{RES} (kWh)	20	500
MP_u (€)	0.18		$y_{D_{RES}}$ (€)	0.01	0.2
a	30	100	n	10	500
r_{min} (€)	0.08	0.12	r (€)	0.08	0.2
x (kWh)	1		-	-	-

In the investigations that were conducted, we assumed that the users are symmetric, i.e., x_n = x, $r_{\min(n)}$ r_{min}, a_n = a, which implies $p_n(.) = p(.)$. In this case, the maximization problem becomes:

$$\max\ \{\mathrm{y_{D_{RES}}} \cdot \mathrm{D_{RES}} - \sum_n [y \cdot r \cdot p(r)]\}$$

$$\Rightarrow \begin{cases} \Sigma_n[y \cdot r \cdot p(r)] < y_{D_{RES}} \cdot D_{RES} \\ D_{RES} \cdot (MPu - y_{D_{RES}}) > 0 \\ r > r_{min} \\ \Sigma_n[y \cdot x \cdot p(r)] = D_{RES} \\ y \in \{0,1\} \end{cases} \tag{7}$$

At the optimal point due to symmetry all targeted users will be offered the same incentives r and will be asked to provide the same x flexibility. It is noticeable that n and r are constrained by the available budget as this is expressed by the product $y_{DRES} \cdot D_{RES}$. They are also constrained by the variables r_{min} and a of the probability function. The analysis was undertaken for a range of values of RES Aggregator's deviation. There is an interesting relation between RES profit and real time deviation, and the investigation of this relation produces meaningful results for all the involved parties. Again, under the current analysis the RES profit expresses the decrease of the RES revenue loss, and the deviation becomes negative when the real time production is less than the one declared on the DAM.

Figure 7a and figure 7b depict the relationship of RES and DR aggregator profits with the deviation for different values of $\mathrm{y_{D_{RES}}}$. It can be seen that the price for the offsetting of every kWh ($\mathrm{y_{D_{RES}}}$) directly affects the aggregator profits. The higher $\mathrm{y_{D_{RES}}}$ the lower the RES profit and the higher the DR profit. For greater deviation values the RES aggregator cannot sell the energy in a small price and this gets more intense near the D_{RES} limit because the cost of user incentivization increases non linearly. Near the D_{RES} limit most or all of the users must be persuaded to participate, and this corresponds to high incentives per user in order to make their probability of participating high. The RES profit is analogous to the reduction of $y_{D_{RES}}$ and D_{RES}

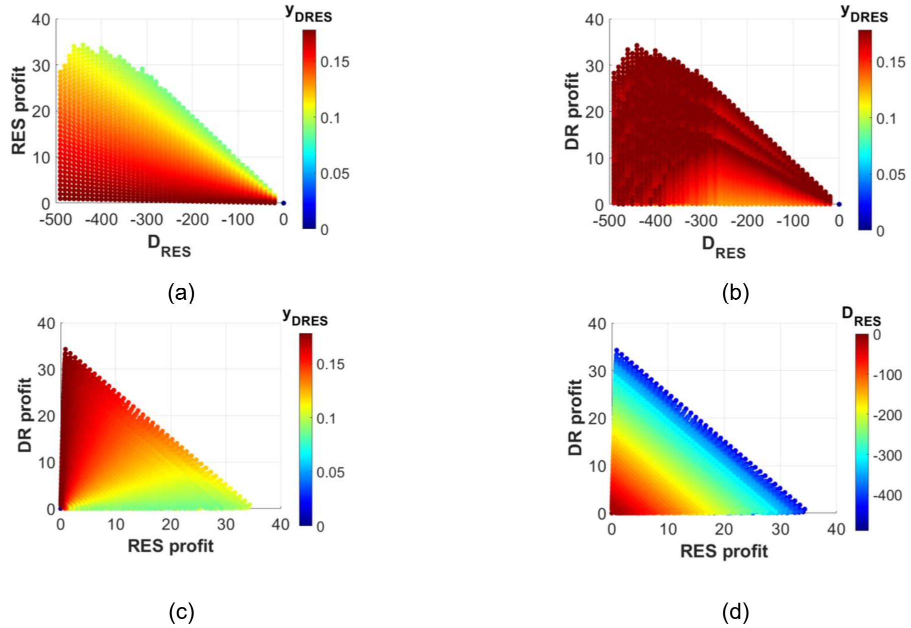


Figure 7: (a) RES and (b) DR Aggregator profit plotted against real time deviation for various values of $y_{D_{RES}}$. RES and DR profits plotted against each other with respect to (c) $y_{D_{RES}}$ and (d) D_{RES}.

for most of the index space but this is not the case for the DR aggregator. His profit drops long before reaching the maximum deviation that he can support and in the extreme values of D_{RES} it gets near zero. This drop is dictated by the non-linear increase of the cost of incentivization when almost all users are required to participate. In any case, the profits of both aggregators always depend heavily on their deal, which is nicely illustrated in Figure 7c: the profit changes hands according to the value of $y_{D_{RES}}$. However, it can also be seen that the DR profit gets easily saturated for small $y_{D_{RES}}$ values. Figure 7d highlights the fact that both aggregators have more room for benefit as the deviation increases. The previous statement considers as a fact that the deviation has occurred due to false predictions. The RES aggregator would rather have zero deviation.

Figure 8 depicts the relationship between Total User Profit (TUP) and the aggregator profits for different values of D_{res} and $y_{D_{RES}}$. TUP is calculated by the following equation:

$$TUP = r \cdot n \cdot p(r) \tag{8}$$

and expresses the total rewards that are received by the end users that shall participate in the DR event. It can be seen that as the deviation becomes greater there is more room for profit both for the aggregators and the users (Figure 8a and c). An interesting result lies in Figure 8b where the RES profit rises exponentially after a certain threshold, particularly in the lower $y_{D_{RES}}$ values. The explanation lies in the fact that when the deviation is quite high the RES aggregator has limited capability to decrease revenue loss, hence the consumers will benefit from increased profits to the detriment of the RES profit. Moreover, the maximum TUP is reduced as $y_{D_{RES}}$ becomes smaller. In Figure 8d it is shown that the DR profit and the TUP go hand in hand in a win-win manner until a threshold is reached where the DR profit drops for a further increase of the TUP.

Figure 9a illustrates the analogy between the DR aggregator profit and the respective revenue. Only when all the users have been selected this profit saturates and even drops in the presence of ample revenue for DR. Figure 9b shows that unwilling users affect the profit of the DR aggregator negatively and begin to drastically affect his profit when all of them must be engaged. Figures 9c and 9d include a y-axis dedicated to the RES aggregator loss, which corresponds to the loss of revenue when compared to the ideal case of zero deviation. It can be seen (in Figure 9c) that through bilateral trading this loss can become smaller, and this capability gradually deteriorates as the deviation becomes greater. The loss is directly related to the selling price $y_{D_{RES}}$. Reduction of the RES loss implies an increase in the DR profit and the total profit of the users (Figure 9d) which illustrates the mutual profit of this scheme for all stakeholders.

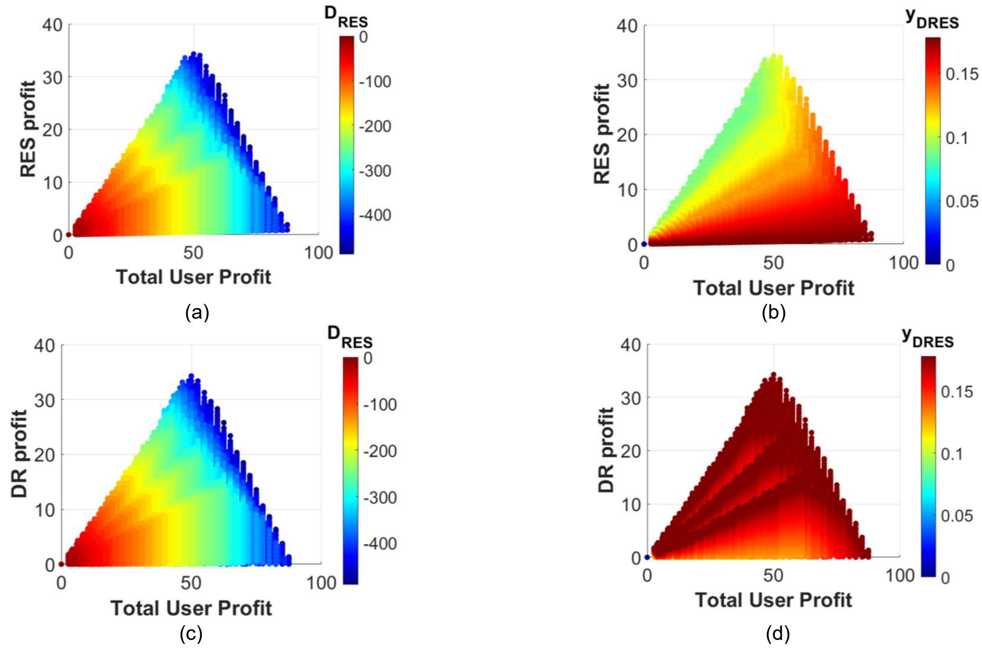


Figure 8: Relationship of RES Profit and DR profit with Total User Profit for various values of (a) real time deviation D_{RES} and (b) bilateral trading agreed value $y_{D_{RES}}$. Again, DR profit plotted against (c) D_{RES} and (d) $y_{D_{RES}}$.

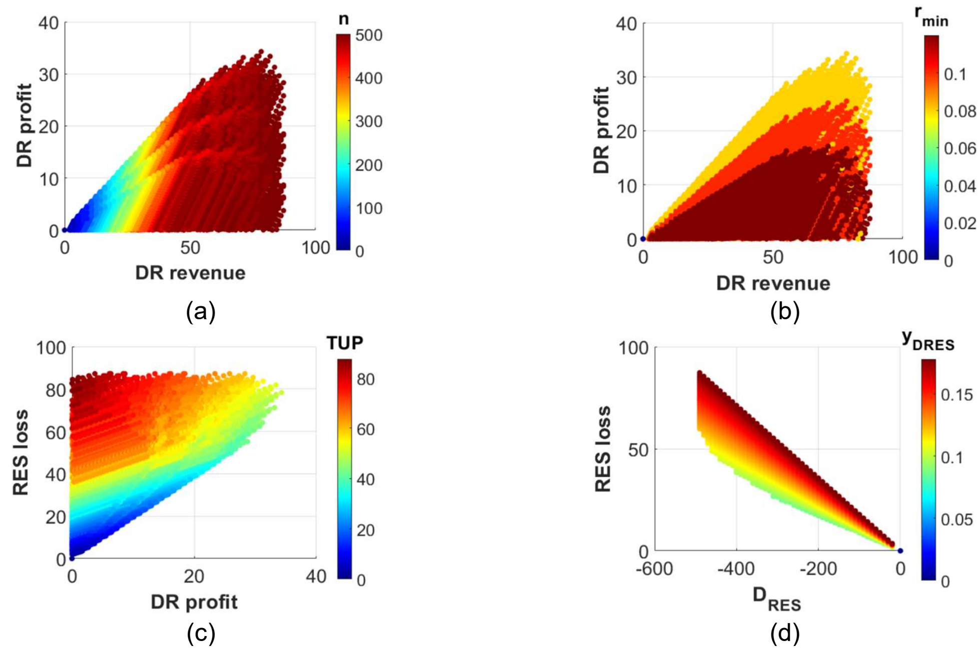


Figure 9: (a) Relationship of DR profit to the DR revenue with regards to (a) the number of selected users n and (b) the minimum acceptable incentives of the users r_{min}. RES loss plotted against (c) DR Profit and Total User Profit and (d) D_{RES} and $y_{D_{RES}}$.

4.6 Guidelines

According to the preceding analysis, the proposed scheme of bilateral trading using DR resources has proven to be beneficial for all the three types of stakeholders involved. However, dividing profits among the three stakeholders can be a complex exercise: everyone will want to maximize his profit; if this is not done carefully, taking into consideration the proper incentivization of the other two entities, the program's effectiveness might be jeopardized. For example, if the RES aggregator does not transfer enough resources to the DR aggregator it might not be beneficial for him to engage at all. Or if the DR aggregator wishes to maximize his profit, the risk of not obtaining the required DR quantity can be greater. To enable a smooth and beneficial cooperation of the three stakeholders, useful guidelines are provided in this section regarding individual profit maximization and mutually beneficial sharing of profit.

The magnitude of the RES deviation that can be offset in the energy market is closely dependent to the user base size and parameters. If the available users are few or unresponsive to incentives, neutralizing a large deviation might be very costly or onerous. On the other hand, a high deviation can be easily taken care of if there are many users willing to contribute. As a result, the RES aggregator can follow a "riskier" policy in the DAM if he is aware that the DR resources are ample and the opposite. It is a strategic advantage of the RES to be able to identify this point in advance and act accordingly in the DAM.

Similarly for the DR aggregator: He should consider the availability of users because his profit might drop in case many users are needed, especially when they are unresponsive. When there is a high deviation, and the user base is not large or adequately responsive, it is critical for the DR aggregator to negotiate high prices in order to realize the DR program and ensure his profit. Low prices of bilateral trading are often risky and not for the benefit of the DR aggregator. However, even if hefty values of DR revenue are available, this is not necessarily beneficial for the DR aggregator for the same reason.

Prudent definition of $y_{D_{RES}}$ is an important part of the bilateral trading process. Very low $y_{D_{RES}}$ values do not provide any profit for DR and a fair starting point would be any value that is close to the DAM price. It should also be mentioned that both aggregators and users have more room for profit in the case of a large deviation.

There is a region in the problem where all three stakeholders achieve significant profits at the same time, as nicely shown in Figure 10. As a result, with proper coordination all three stakeholders can benefit from a deviation. In the absence of coordination, any one of the three players can benefit disproportionally, thus drastically deteriorating the profits of one of the others or both of them. In other words, coordination is not only about the two aggregators but involves the users as well. Users that are not positively spaced towards this scheme and want to absorb as much profit as possible essentially ruin this opportunity.

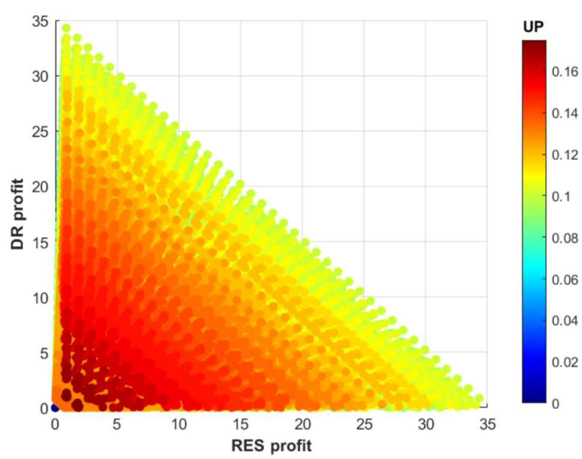


Figure 10: Relationship of the profits of the three stakeholders: RES aggregator, DR aggregator and user.

4.7 Incentives component integration

In this section, the integration of the incentives component in the iFLEX assistant is documented and various considerations for its effective implementation will be discussed. This exposition includes a more detailed description than the one provided in D4.6, specifically for the Greek pilot case. Several considerations have already been discussed in D5.3, regarding the practical issues in the pilot phase of the project. However, additional evaluation has been conducted in this subject in light of the integration to be performed, which is described below. The analysis and documentation is composed of two subsections. The first concerns the initial stage of the pilot, where incentives are provided without using an optimization algorithm since the user parameters are not known. The scope of this stage is the discovery (i.e. learning) of the model of the users.

The second subsection concerns the second stage of the pilot, where ordered targeting takes place. Here, the data exchanges between the incentives' component and the rest of the iFLEX assistant are discussed along with the main optimization algorithm.

4.7.1 Initial incentives considerations

In D5.3 we introduced and evaluated an algorithm to identify the user DR parameters of each user without previous knowledge whatsoever. With those parameters captured, the value p (success probability) of each user will be fully known. Thus, the real user will be modelled, and the optimization algorithms of the provider will be in position to provide the optimal targeting. The basic concept of the algorithm was provided, along with the respective mathematical formulas. Moreover, two schemes of incentives' provision were examined for the initial model learning phase:

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

The predictive method has proven to be very fast in terms of convergence to the user parameters. However, as shown in D5.3, the incentives' provision ends up becoming almost constant around the detected r_{min} which can be either an advantage or a drawback regarding whether we want the user to feel as if he is receiving random or steady incentives. Thus, additional studies were conducted for the purpose of integration in order to obtain an alternative means of incentives' provision (during the learning phase). This shall involve incentives that vary significantly through the various attempts and can be accomplished by utilizing as a basis a sinusoidal function. Therefore, two additional schemes are proposed and tested:

3) reversing sinusoidal (open loop procedure)
4) boosting reversing sinusoidal (closed loop procedure)

In the reversing sinusoidal scheme (Figure 11), the incentives provision follows a sinusoidal pattern that reverses its sign every second attempt:

$$r = \begin{cases} o_s \cdot \sin(m * \omega - \varphi), & m \rightarrow even \\ -o_s \cdot \sin(m * \omega - \varphi), & m \rightarrow odd \end{cases}$$

where o_s is the maximum span of the offers that are provided to the user, ranging from a minimum to a maximum value: $o_s = o_{max} - o_{min}$, m is the attempt index, ω and φ parameters that define the sinusoidal waveform characteristics, namely the frequency and the initial phase.

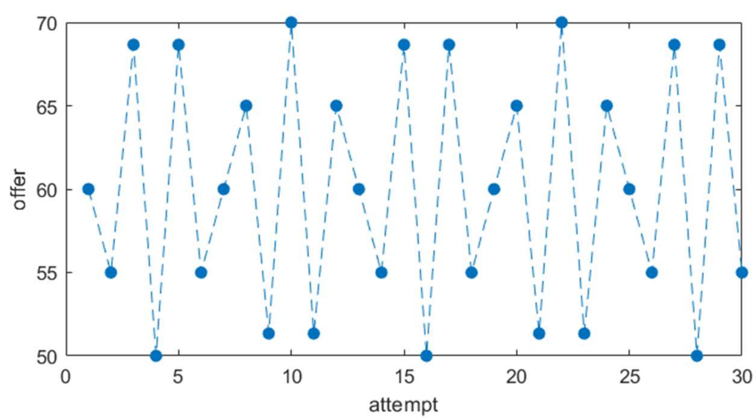


Figure 11: Example reversing sinusoidal scheme waveform for indicative values

In the boosting sinusoidal scheme (Figure 12), the incentives provision is similar to the previous case but with the difference that the offer span is smaller and a rise factor c is added to the formulation, which increases when the user responds negatively and decreases when the user responds positively.

$$r = \begin{cases} o_s \cdot \sin(m * \omega - \varphi) + c, & m \rightarrow even \\ -o_s \cdot \sin(m * \omega - \varphi) + c, & m \rightarrow odd \end{cases}$$

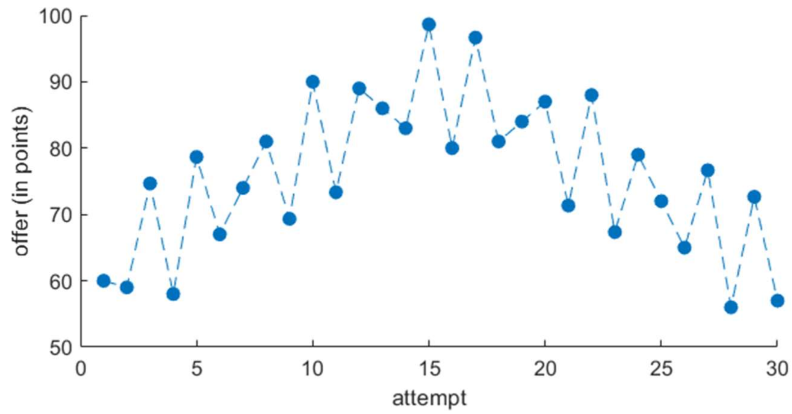


Figure 12: Example boosting reversing sinusoidal scheme waveform for indicative values

For testing purposes, we employ the random provision method along with the reversing sinusoidal one and compare their convergence characteristics. We employ the algorithms 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 13 illustrates the shapes of the probability function for the three random users A, B and C.

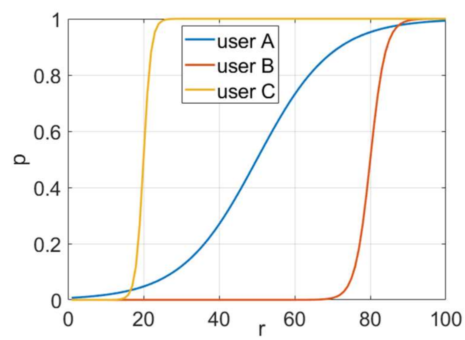
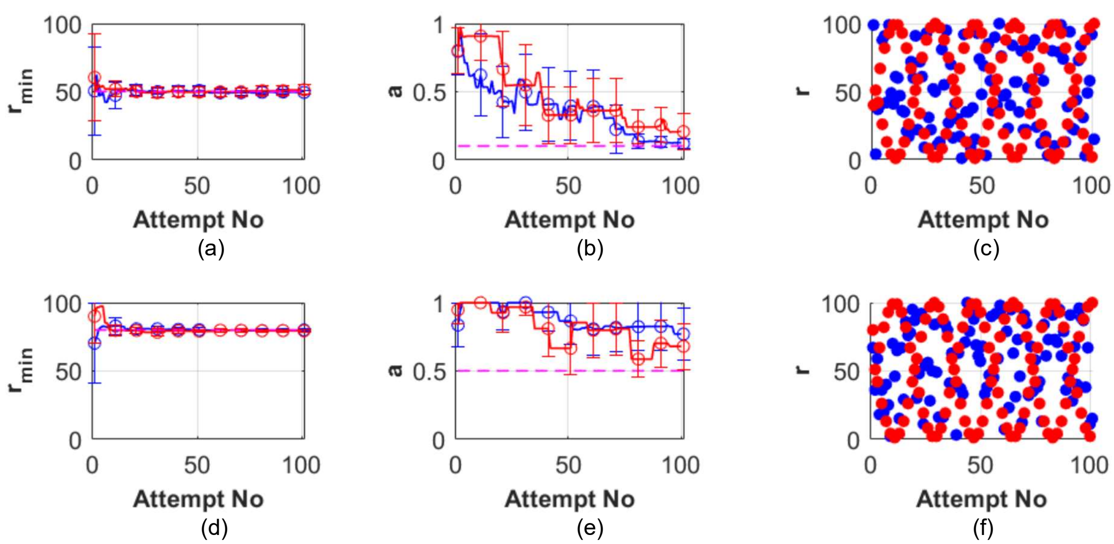


Figure 13: Probability function shape illustration for the random users A, B and C

The procedure is repeated 10 times, the results are averaged and illustrated in Figure 14. Blue colour corresponds to random offering and red colour to the reversing sinusoidal method. It can be seen that both methods have similar performance characteristics.



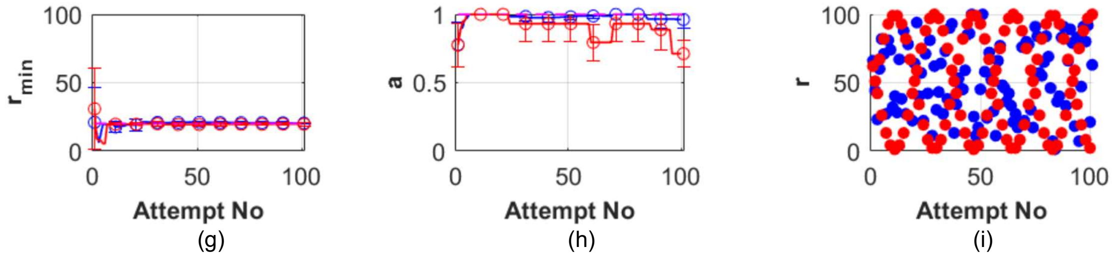


Figure 14: Parameter identification efficiency test for the 3 random users (user A: a, b, c – user B: d, e, f – user C: g, h, i). The first column (a, d, g) illustrates the r_{min} convergence, the second column (b, e, h) the *a* convergence and the third column (c, f, i) shows the values of the *r* offerings. Blue color corresponds to the random method and red colour to the reversing sinusoidal one.

A more important set of results can be derived from the comparison of the boosting reversing sinusoidal (closed loop) scheme to the random one (Figure 15). The test settings are the same as in the previous case. It can be seen here that the boosting reversing sinusoidal scheme has better performance characteristics compared to the random method. While convergence to r_{min} is fast in both cases, discovery of a is faster and more stable.

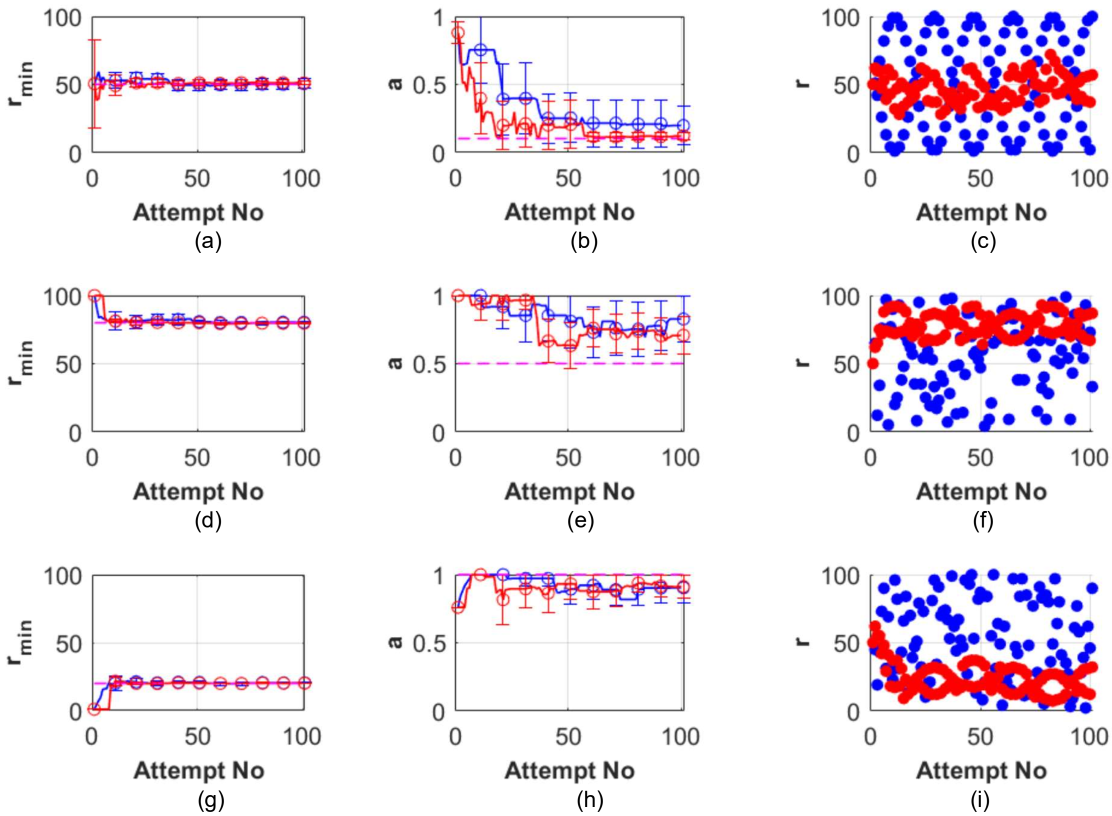


Figure 15: Parameter identification efficiency test for the 3 random users (user A: a, b, c – user B: d, e, f – user C: g, h, i). The first column (a, d, g) illustrates the r_{min} convergence, the second column (b, e, h) the *a* convergence and the third column (c, f, i) shows the values of the *r* offerings. Blue color corresponds to the random method and red color to the boosting reversing sinusoidal one.

Finally, the two closed loop methods that are better than the random scheme, namely the predictive and boosting reversing sinusoidal ones are compared to each other under the same testing settings to discover their strong and weak points. It can be seen that the latter is more efficient for users with small a parameters and the former for users with greater a parameters, as far as the responsiveness parameter a is concerned. Regarding the minimum acceptable incentives' parameter r_{min} the predictive methos is somewhat faster, but still similar to the other one.

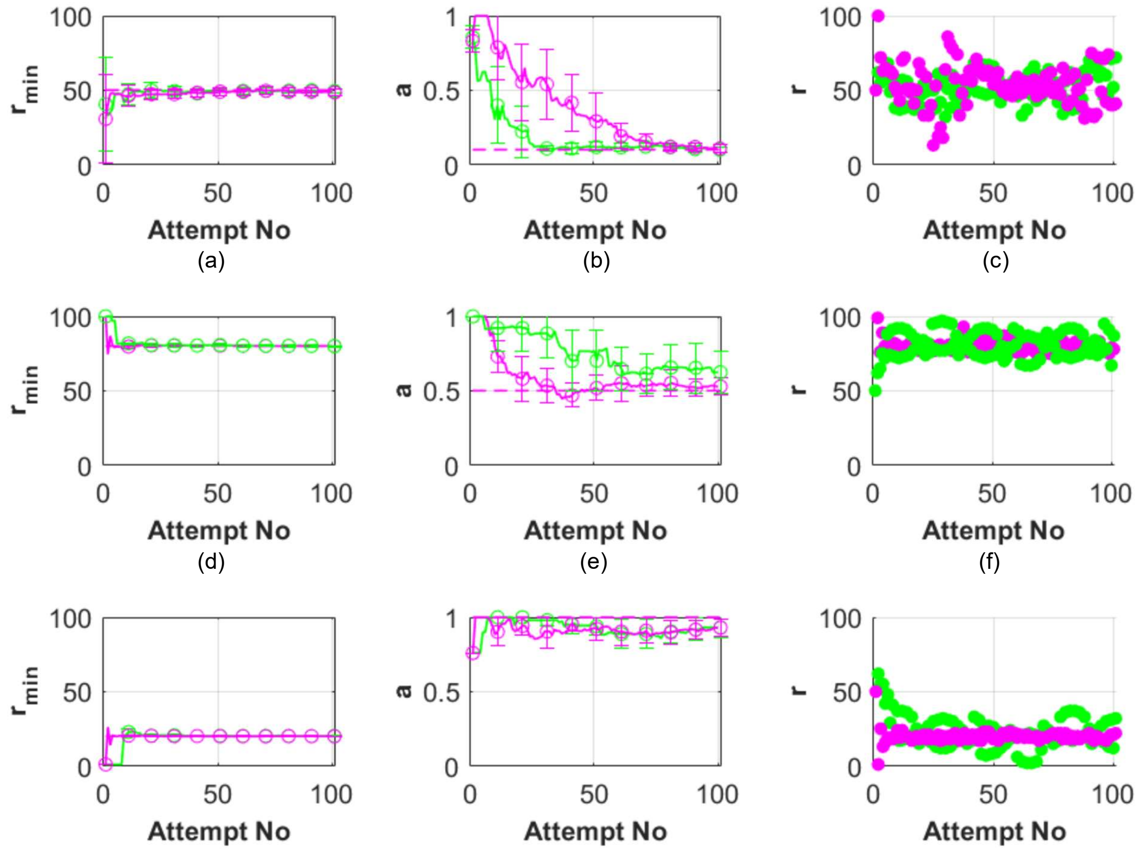


Figure 16: Parameter identification efficiency test for the 3 random users (user A: a, b, c – user B: d, e, f – user C: g, h, i). The first column (a, d, g) illustrates the r_{min} convergence, the second column (b, e, h) the *a* convergence and the third column (c, f, i) shows the values of the *r* offerings. Green color corresponds to the boosting reversing sinusoidal method and magenta color to the predictive one.

The following table summarizes the results from the various methods proposed (also combining the results from D5.3). It can be seen that the closed loop methods are overall attractive, whereas the open loop ones are not adequate for the user responsiveness tracking.

Table 6: Summary of various methods characteristics

Method	Participation feedback	r_{min} convergence	a convergence	Pattern
random offers	open loop	good	poor	alternating
predictive method	closed loop	good	good - (better in big a)	converging
reversing sinusoidal	open loop	good	poor	alternating
boosting rev. sinus.	closed loop	good	good – (better in small a)	alternating

Taking into account all the above results, it is concluded that the most effective method is the boosting reversing sinusoidal one. This is because it is of more critical importance to track the a parameter effectively in cases where its value is small, than the opposite. When this parameter holds a large value, then the sigmoid function is similar to a step function and only a small difference in incentives may provide 100% probability of participation. The exact opposite is the case when a is small: the span of incentives is great, and it is important to be aware of the exact incentives required to achieve a specific probability of participation. This is nicely shown in the figure below. In the piloting phase of the project, the boosting reversing sinusoidal scheme shall be initially employed.

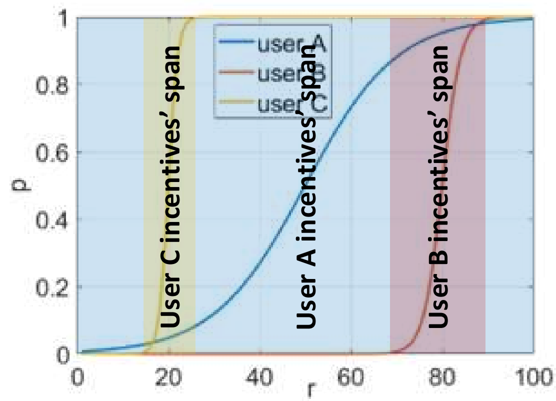


Figure 17: Incentives' span among 0% and 100% probabilities of participation for the three aforementioned users.

4.7.2 Main optimization stage

In the next stage of piloting, the users shall be properly targeted since their modelling characteristics will be known. Here, we shall seek for the minimum expected total DR incentives (reward) that are necessary for the flexibility aggregator to meet a particular expected total flexibility X_E threshold, while also maintaining the budget constraint B. This problem can be formulated (similarly as in D5.3) as follows:

$$\begin{cases} \min \sum_n y_n \cdot r_n \cdot p_n(r_n) \\ s.t. \begin{array}{l} \sum_n y_n \cdot x_n \cdot p_n\,(r_n) \geq X_E \\ \sum_n y_n \cdot r_n \cdot p_n(r_n) \leq B \end{array} \end{cases} \tag{9}$$

Regarding the user parameters a and r_{min} that are involved in $p_n(r_n)$, it is considered that they may be different for the same user according to the time of day that the DR event takes place. For example, switching off the water electric boiler in the morning might involve less comfort loss than switching it off in the evening, affecting respectively the cost of incentivization. For this reason, we shall assume that each user is characterized by three (3) sets of parameters that correspond to the morning (6:00 to 12:00), evening (12:00 to 18:00), and night (18:00 to 0:00), that are different. All the participation data from DR events that occur within the time frame of either the morning, evening, or night, will equally contribute to the learning process of the respective user parameters.

In order for the incentives' optimization to take place, specific data should be exchanged between the algorithm and the rest of the iFLEX framework. A general overview of the relevant data has been provided in D4.6. Here, they will be discussed in a more detailed and pilot-specific manner. These data concern the following:

- **Flexibility potential**. This concerns the possible energy potential of the electric device, expressed in kWh. In the model it is denoted by x_n. This is an outcome of the forecasting capabilities of the iFLEX assistant and serves as an input to the optimization algorithm.
- **Incentives' offer**. This is about the monetary incentives to be provided to the users, which in this case will pe points. It is denoted by r_n. This is an outcome of the optimization algorithm and shall be provided as an input to the rest of the components of the iFLEX assistant.
- **User targeting**. The optimization scheme targets users for DR using the binary variable y_n. This is an output of the optimization.
- **Response to DR event.** This constitutes the response of the iFLEX assistant after a DR event is over. The algorithm is notified whether the user accepted the invitation or not. This response might be accompanied by the amount of flexibility harnessed, subject to the type of device employed in the piloting phase. This information is required for validation purposes of the developed algorithms.
- **Budget.** The total available budget of the DR aggregator B for a specific DR event, or a series of DR events. In the pilot, instead of directly offered monetary incentives, this budget will be defined as a sum of points to be distributed to the users and shall reflect a real gift such as e.g. a laptop computer (Section

3.3 of D5.3). For the piloting phase of this project, the budget will be decided beforehand according to the sum of the DR attempts that will take place and the usual RES aggregator imbalances. In each DR event the available budget will be fully defined, and the used budget will be communicated back to the DR aggregator.

- **Total flexibility request**. The total flexibility X_E that will be requested by the RES aggregator will be provided as an input to the optimization problem and shall depend on the imbalances the RES aggregator has in this specific slot.

The optimal targeting optimization problem cannot be directly solved with optimization algorithms such as mixed-integer linear programming. The incentives r_n are part of a sum within an exponent of another sum and this increases the complexity significantly. An optimization algorithm that would be both easily deployable and effective could be a heuristic such as Differential Evolution (DE) or Genetic Algorithm (GA) etc. These algorithms improve the candidate solution in iterations without making any assumptions about the problem to be optimized. They work with populations of solutions that progress towards the solution in every iteration. For the needs of the piloting phase such a heuristic will be employed. Performance issues (regarding convergence) need not to be considered here since the number of users is small. A next step of this investigation, for research purposes, could include an exploration of the effectiveness of various optimization algorithms for this problem when it includes a large number of users.

4.8 Summary

In this chapter, a bilateral trading scheme between a RES and a DR aggregator was investigated under a dual-tariff penalty scheme for RES energy imbalances between the real-time production and the day-ahead market declaration. Under a bilateral agreement between RES and DR aggregators, the DR aggregator internalizes the RES imbalance in its profit maximization strategy and, depending on the real-time scenario, aggregates the required flexibility by appropriately incentivizing his end-users. We considered uncertainty in the end-user participation in DR events subject to their offered rewards. We defined an optimization framework to analyze the trade-off among maximizing the profit of RES and DR aggregators and appropriately incentivizing the users. Depending on the size and the sign of the RES energy imbalance, different profit sharing among RES / DR aggregators and different distributions of user rewards emerge. Through extensive numerical analysis, we found that the studied bilateral scheme can be mutually profitable for all stakeholders involved. Insights are also provided on the dependence of the trading strategy of RES and DR aggregators with the user-base flexibility characteristics. Guidelines have been proposed so that such bilateral agreements between RES and DR aggregators can be considered in every-day grid operation.

Furthermore, considerations related to the incentives' component integration in the pilots of the project have been provided. Additional incentives' provision schemes have been proposed regarding the initial phase and one of them has proven to be more beneficial in the pilot practical settings. Also, the ordered targeting phase with its optimization framework has been discussed in more detail, highlighting the relevant implementation factors. As a final remark, it should be reminded that (as explained in detail in D5.3) the rewards (incentives) calculated by means of the model of the Greek pilot are *not* "paid" directly to the users. Instead, users participate in a *lottery* (say per month), in which each user's probability to win is proportional to his total rewards accumulated in this period and the value of the prize awarded equals the sum of these total rewards across all users.

5. Final Model and Incentives' Scheme for the Slovenian Pilot

5.1 The Context

The models and incentives' schemes for the Slovenian pilot have been thoroughly described in D5.3 and they were published in (Papaioannou and Stamoulis, 2022). Here, we describe the basic context and the basic decentralized model that can be applicable in realistic cases. We also introduce an approach for allocating the optimal (total) flexibility per user (as determined by means of this model) to the flexible assets of the user, i.e. his appliances. We consider prosumers with PV panels (i.e., photovoltaic electricity generation) but with no electricity storage capacity. The PV energy that cannot be consumed locally can be injected into the grid, potentially at a different feed-in tariff than the price of the electricity consumed. Additionally, (Home Energy Management Systems) HEMSs are installed at prosumer/consumer premises. HEMS provide readings from individual devices at residential premises, e.g., heat pumps and boilers, and readings from sensors for comfort (e.g., temperature, humidity).

In this pilot, flexibility is expected to be mostly provided based on implicit DR signals, which practically are high network and/or retail electricity tariffs for specific hours announced one day ahead. The users are expected to modify their electricity-consumption schedules in response to these higher tariffs, so as to minimize their electricity bill, and thus offer flexibility. These tariffs could potentially be combined or alternated with rewards for the flexibility provided in the flexibility events. Our model presented below can accommodate both cases of DR.

In addition, messages are to be sent to users as energy consumption feedback (i.e., energy advice) and encouragement for reacting upon these signals. The users practically cannot opt-out. However, they are free to choose their own self-optimizing way to react to DR signals, by manually adjusting or not their electricity consumption schedule accordingly, or by resorting to automated flexibility management (e.g., iFLEX assistant) that is able through HEMS to optimally adjust the electricity consumption according to the DR signals. Hence, while users cannot declare opting-out, they may opt out in practice by not responding to DR signals if this is preferable for them. Slovenian users will be able to choose which activities involving electricity consumption to shift in time or cancel, in order to participate in the flexibility event.

5.2 The Decentralized 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 (PVs), 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.

5.2.1 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 a reward *r* per flexibility unit provided thereto. Then, the objective of the DR aggregator is to minimize the total amount of flexibility rewards, 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 $\boldsymbol{x}_{n,1} = \left\{x_{n,1}^t\right\}, \forall t \in \mathcal{T}$ is the updated daily consumption schedule for consumer n subject to the flexibility event. Therefore, the DR aggregator's optimization problem is as follows:

$$\textbf{Minimize: } \sum_{n \in \mathcal{N}} r x_n^\tau \tag{10}$$

$$\textbf{s.t. } \sum_{n \in \mathcal{N}} x_n^\tau \geq X^\tau \tag{11}$$

$$x_n^\tau \leq x_{n,0}^\tau + w_n^\tau,\ \forall n \in \mathcal{N} \tag{12}$$

This problem formulation can also work for the case where no flexibility rewards are offered, but only peak electricity tariffs at the time slot of interest, by setting *r*=1. In this case, only the flexibilities of the users would be sought by the DR aggregator, who would just aim to aggregate the minimum desirable flexibility.

5.2.2 The User's problem

We assume that users are offered by the DR aggregator incentives r per flexibility unit at time slot τ, which can also be 0 in case that implicit DR, i.e., peak electricity tariffs are employed for aggregating flexibility. Then each user n has to select is optimal flexibility vector x_n, by solving the following problem:

$$\begin{aligned}\textbf{Maximize: } & r x_n^{\tau} + U_n(\mathbf{x}_{n,0} - \mathbf{x}_n) - U_n(\mathbf{x}_{n,0}) \\ & - \sum_{t\in\mathcal{T}, x_{n,0}^t - x_n^t \geq w_n^t} (x_{n,0}^t - x_n^t - w_n^t)\psi^t + \sum_{t\in\mathcal{T}, x_{n,0}^t \geq w_n^t} x_{n,0}^t \psi^t \\ & + \sum_{t\in\mathcal{T}, 0 < x_{n,0}^t - x_n^t < w_n^t} (w_n^t - x_{n,0}^t + x_n^t)\phi^t \\ & \qquad - \sum_{t\in\mathcal{T}, 0 < x_{n,0}^t < w_n^t} (w_n^t - x_{n,0}^t)\phi^t \end{aligned} \tag{13}$$

$U_n(\boldsymbol{x}_{n,0})$ is the user utility of consumer *n* due to the baseline electricity consumption vector $\boldsymbol{x}_{n,0}$, while $U_n(\mathbf{x}_{n,0}-\mathbf{x}_n)$ is the user utility of consumer *n* after providing flexibility vector $\boldsymbol{x}_n$. $\boldsymbol{\psi}$ is the electricity price vector per time slot (usually one hour) announced at least one day ahead. $\boldsymbol{\varphi}$ is the feed-in tariff vector per time slot (usually one hour) for injecting energy to the grid from renewable sources. Also, $\boldsymbol{w}_n$ is the energy production vector per time slot (usually one hour) for consumer *n*. Note that only that the energy that is drawn from (resp. injected to) the grid is actually charged (resp. paid). The objective function in (13) expresses the total net benefit (profit) of the user, combining the monetary gains and losses of the user (from DR incentives, energy bill savings, and feed-in tariffs), with the user losses in utility (i.e. in comfort) due to reduced energy consumption as a result of flexibility.

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

- Individual Rationality (IR): The net benefit from participating in DR should be non-negative.
- Incentive Compatibility (IC): The net benefit from participating in DR should be higher than or equal to that when not participating, or equivalently the difference of these two net benefit values should be non-negative; this amounts to accepting a solution to the maximization problem (13), so that the maximized quantity is positive. As explained in D5.3, IR and IC conditions are concurrently met when condition (13) ≥ 0 is true.

Our analysis to follow is applicable to increasing and differentiable user utility function. Nevertheless, in our analysis of D5.3, we employ the following utility $U(\cdot)$:

$$U_n(\mathbf{x}_n) = \sum_{t\in\mathcal{T}} \beta_n^t (x_{n,0}^t - x_n^t) \tag{14}$$

where $\beta_n^t = x_{n,0}^t / \max\{x_n\}$. According to this function, a reduction (resp. increase) in energy consumption at a certain time slot results in loss (resp. gain) of comfort, and respectively 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.

5.2.3 Distributed Algorithm

As explained in detail in D5.3, in the case where user utility functions are not known, the DR aggregator and the user should solve their individual problems, i.e., (10) for the DR aggregator and (13) 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.

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

$$x_n^{t,k+1} = \min\{x_{n,0}^t,\ x_n^{t,k} + \xi(r^k + (-\beta^t) + \psi^t \mathbf{1}(x_{n,0}^t - x_n^t - w^t) - \phi^t \mathbf{1}(w^t - x_{n,0}^t + x_n^t)\} \quad (15)$$

$\mathbf{1}(\cdot)$ is an indicator function, which equals 1 if its argument is greater than zero, or 0 otherwise. Then, DR aggregator updates the incentives r per unit of flexibility according to the formula below, according to which the offered incentives in the next step are raised (resp. lowered) if the total flexibility attained due to the "present" is less than (resp. greater than) the target value. The step decrease (resp. increase) of the incentives parameter r^k is proportional to the surplus (resp. deficit) of flexibility, in order to attain convergence of r^k to its optimal value whereby the targeted total flexibility is met exactly, and it is given by the formula below:

$$r^{k+1} = \max\left\{r^k + \xi\left(X^\tau - \sum_{n\in\mathcal{N}} x_n^\tau\right),\ 0\right\} \quad (16)$$

At the end of the round, the DR aggregator sets $r^k = r^{k+1}$ and each customer $n \in \mathcal{N}$ sets $x_n^{t,k} = x_n^{t,k+1}$.

In the case of implicit DR, no rewards are employed. Then, the appropriate peak tariff ψ^τ for the time slot of interest τ has to be determined by the DR aggregator, while $r^k = 0$. In this case, equation (16) is replaced by the following:

$$\psi^{\tau,k+1} = max\left\{\psi^{\tau,k} + \xi\left(X^\tau - \sum_{n\in\mathcal{N}} x_n^\tau\right), 0\right\} \quad (17)$$

5.3 Automated Flexibility Management or Energy Advice

So far, our optimization models have focused on deriving the optimal flexibility x_n^τ to be provided by each prosumer $n \in \mathcal{N}$ at the time slot of interest τ. For each prosumer $n \in \mathcal{N}$, we assume a set of flexible assets $\mathcal{A}_n$ at his premises. For simplicity, we take each flexible asset $m \in \mathcal{A}_{n,0}^\tau \subseteq \mathcal{A}_n$ to have only two states ON/OFF, consuming energy $a^\tau_{n,m}$ when ON during the time slot of interest τ, or alternatively providing the same energy amount as flexibility when OFF. In other words, $a^\tau_{n,m}$ is the flexibility potential of a flexible asset *m* of user *n* during the time slot of interest τ. Then, in order to find the optimal state of these flexible assets to aggregate the desired energy flexibility x_n^τ at the time slot of interest τ, in the full-info optimization model of the aggregator (13), we would have to express x_n^τ as:

$$x_n^\tau = \sum_{m\hat{\mathrm{I}}\,\mathcal{A}_{n,0}} a_{n,m} y_{n,m}^\tau\ , \quad (18)$$

and replace it in the equations of the relevant optimization problem, where $y_{n,m}^\tau \in \{0,1\}$ would be a new vector of decision variables x_n^τ similarly to the approach followed in (Li, Chen & Low, 2011). Thus, the total flexibility x_n^τ to be offered by user *n* at time slot τ is the sum of the flexibility potential of all appliances for which $y_{n,m}^\tau = 1$. Therefore, for the time slot of interest τ, the number of control variables of the problem would be multiplied by $|\mathcal{A}_{n,0}^\tau|$, thus increasing the computational complexity of the original user problem. Most importantly, this would require disclosure of $\mathcal{A}_{n,0}^\tau$ to the DR aggregator, which is not desirable for privacy reasons.

A suboptimal, yet *privacy-friendly*, approach would be to run the distributed iterative algorithm of Section 5.2.3 between the aggregator and the user until convergence and then to map the attained flexibility x_n^τ of user n to the most proximal combination of flexible assets in the set $\mathcal{A}_{n,0}^\tau$ at the user premises that can provide this flexibility. The complexity of deriving this mapping exhaustively would be exponential and equal to $2^{|\mathcal{A}_{n,0}^\tau|}$; however, the number $|\mathcal{A}_{n,0}^\tau|$ of flexible assets is expected to be small and therefore the solution will be computationally light. The development of greedy approximations (useful for cases of many flexible assets) is left for future research.

6. Final Model and Incentives' Scheme for the Finnish Pilot

6.1 Shared Total Energy Bill – Single Flexibility Slot

We consider an apartment building containing multiple residential flats. The residents of the building share the bill for the heating and electricity consumption both in the common spaces of the building and inside their own flats. This could be the case for a public apartment building, such as a student dormitory or a public house for low-income families. Thermal energy is provided to the apartment building by a District Heating Operator (DHO) in the form of hot water in the apartment radiators. Moreover, large exhaust fan heaters that operate on electricity are installed in the common spaces of the building and contribute heating energy during wintertime. It is assumed that these exhaust fan heaters operate in full power during all winter, but their thermal energy is not enough to maintain a sufficiently high temperature inside the building. In such an apartment building, energy flexibility can be provided on the basis of the thermal capacity and the thermal insulation of the building. Specifically, we consider the case where district heating at the building is turned off for a specific period of time. This results in interior temperature drop for the flats of the building, which negatively affects the user utility (i.e., satisfaction) of the residents of the flats. Residents of different flats have their own comfort constraints on the lowest interior temperature allowed, each of which bounds the amount of energy flexibility that can be provided by this approach. Moreover, residents of the building may counteract this approach for energy flexibility by increasing the electricity consumption in their own flats, e.g., by turning on some electric exhaust fan heaters, electric blankets, etc. or by engaging into activities that raise interior temperature, such as cooking, in order to compensate for the heat loss. However, such a counteraction is reflected in the electricity bill of the respective flat. The occupants might also decrease their electricity consumption at the time slot of interest, e.g., by leaving the apartment. Note that no smart meters are assumed to be present for the flats of the apartment building. Although, no individual electricity consumption is metered per flat, this model investigates user incentives for providing cross-energy flexibility.

6.1.1 The Basic Model: Shared Total Energy Bill under Full Information

In the context of Section 6.1, assume a set $\mathcal{N}$ of flats in the apartment building, with each $n \in \mathcal{N}$ representing all occupants of an individual flat. Assume that time is slotted. Let $\boldsymbol{x}_{n,0}$ denote the total baseline energy consumption vector per time slot (i.e., electricity and district heating energy on the aggregate). We consider the flexibility management mechanism that was described in Section 6.1. Note that while cutting off district heating energy corresponds to an (almost) equal reduction in thermal energy per flat n, the electricity consumption per flat may be different. A user utility function $U_n(.)$ reflects the satisfaction for the total energy consumption of flat n. Therefore, a temperature drop due to the total decrease of energy consumption results in loss of user utility for each flat. The users of flat n have comfort constraints for the interior temperature, i.e., $T_n^{min} \leq T_n \leq T_n^{max.}$ We assume that for occupants of flat n that provides flexibility x_n^τ at time slot τ, there is a utility drop equal to $U(x_{n,0}^\tau) - U(x_{n,0}^\tau - x_n^\tau)$ The bill for the total energy consumption, calculated by function $C(.)$, is shared evenly over all apartments of the building.

Let τ to be the slot of interest for procuring flexibility. We assume that the users receive a reward r proportional to the units of flexibility that they provide. The total amount of flexibility rewards cannot exceed the budget B. We denote as x_n^τ the energy flexibility provided by users in flat n at time slot τ. Then, the overall aggregator's problem is to maximize the aggregate energy flexibility by all users at time slot τ within the available budget B. The overall problem of the aggregator/flexibility manager can be formulated as follows:

Aggregator's problem

$$\begin{aligned} \textbf{Maximize:}\ & \sum_{n\in\mathcal{N}} x_n^\tau \\ \textbf{s.t.}\ & r x_n^\tau + U_n(x_{n,0}^\tau - x_n^\tau) - U_n(x_{n,0}^\tau) - c\left(\sum_{n\in\mathcal{N}} (x_{n,0}^\tau - x_n^\tau)\right) + c\left(\sum_{n\in\mathcal{N}} x_{n,0}^\tau\right) \geq 0,\ \forall n \in \mathcal{N} \\ & T_n^{min} \leq T_n^{in} \leq T_n^{max},\ \forall n \in \mathcal{N} \\ & \sum_{n\in\mathcal{N}} r x_n^\tau \leq B \end{aligned} \tag{19}$$

According to the first constraint, flat owner *n* should have a positive (or at least zero) net benefit difference from flexibility provision, i.e., flexibility rewards plus bill savings minus user utility drop. However, this formulation necessitates knowledge of the user utility functions of all users, as well as their comfort constraints. We relax this requirement in the next subsection.

Deriving from (Li, Chen & Low, 2011), the indoor temperature may be formulated as a function of the energy flexibility x^t_n provided by user n at a time slot t as follows:

$$T^{in,t}(x_n^t) = (1-a)T_n^{in} + aT^{out} + \beta(x_{n,0}^t - x_n^t)$$

where α, β are parameters related to the heat transfer of the building and the efficiency of the heating device respectively.

6.1.2 Leader-Follower Game for Shared Total Energy Bill and Hidden Utility Information

When the user utility functions of the flat owners are not known to the DR aggregator that performs flexibility management, then the aggregator's problem is to select reward *r* per flexibility unit, so as to maximize flexibility and the problem of each flat owner *n* is to select x_n^τ, so as to maximize its own net benefit within the temperature constraints. The problem of each flat owner, also referred to as user, is to optimally select its energy flexibility x_n^τ, so that it maximizes its net benefit within its comfort constraints for the announced reward per energy flexibility *r*. This setting corresponds to a leader-follower game, formulated below.

Aggregator's problem

$$\begin{aligned} &\textbf{Maximize:} \sum_{n\in\mathcal{N}} x_n^\tau \\ &\textbf{s.t.} \quad r\sum_{n\in\mathcal{N}} x_n^\tau \le B \end{aligned} \tag{20}$$

User's problem

$$\begin{aligned} &\text{Maximize:} \; rx_n^\tau + U_n(x_{n,0}^\tau - x_n^\tau) - U_n(x_{n,0}^\tau) - c\left(\sum_{n\in\mathcal{N}}\left(x_{n,0}^t - x_n^t\right)\right) + c\left(\sum_{n\in\mathcal{N}} x_{n,0}^t\right) \\ &\text{s.t.} \; T_n^{min} \le T_n^{in} \le T_n^{max} \end{aligned} \tag{21}$$

This problem can be mathematically solved by backwards induction. That is, the user's problem is solved first for each user *n*, to find the optimal flexibility x_n, as a function of r^*, 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, $\forall n \in N$ to r^*, were known and expressed in closed form. However, this is a very restrictive assumption. Hence, we resort to a distributed iterative algorithm for deriving the desired equilibrium point.

6.1.3 Distributed Algorithm

As already explained, in the case where user utility functions are unknown, then the DR aggregator and the user should solve their individual problems, i.e., (2) for the DR aggregator and (21) for the user respectively. For this purpose, we introduce the following distributed iterative approach: The DR aggregator and the consumers jointly compute an equilibrium based on a gradient approximation 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.

At the beginning of each round k, the DR aggregator announces the per unit of flexibility incentives *r(k)*. Each user *n* updates his offered flexibility $x_n^\tau(k+1)$ for round *k+1* according to the formula below and announces it to the DR aggregator.

$$x^\tau_n(k+1) = \min\{x^\tau_{n,0}, x_n^\tau(k) + \gamma\cdot(1+(\mu-\lambda)r(k) + \lambda(U_n'(x^\tau_{n,0} - x^\tau_n) - c'(\textstyle\sum_{n\in N} x_{n,0}^\tau - x_n^\tau)) - \nu T^{in\prime}(x^\tau_n(k)))\}$$

λ, μ, ν are Karush-Kuhn-Tucker (KKT) multipliers that can optimally solve the problem when KKT conditions hold. *U΄(.), c΄(.)* are the first-order derivatives of the user utility and cost functions respectively, assuming that *U(.)* and *c(.)* are differentiable. $T^{in}(x^{\tau}_n)$ is a function of the indoor temperature given the energy flexibility x^{τ}_n provided by user *n* at time slot *τ*; thus, $T^{in}{}'(.)$ is its first order derivative, assuming that $T^{in}(.)$ is differentiable. Then, DR aggregator updates the per unit of flexibility incentives *r* at the end of round *k* according to the formula below and announces it at the beginning of round *k+1*.

$$r(k+1) = \min\left\{B / \sum_{n\in N} x_n^{\tau}(k),\ r(k)\ + \gamma B / \sum_{n\in N} x_n^{\tau}(k)\right\} \tag{22}$$

This iterative process stops when the values of *r* and $x^{\tau}_n, \forall n \in N$ converge, that is the difference of the respective value in two consecutive rounds is below a certain small threshold.

6.1.4 Numerical Evaluation

We consider the REDD dataset of 6 houses of (Kotler & Johnson, 2011) to represent the flats of the building of interest. We assume that the consumption in the dataset corresponds to total consumption of thermal and electric energy. The baseline consumption of the flats is depicted in Figure 18.

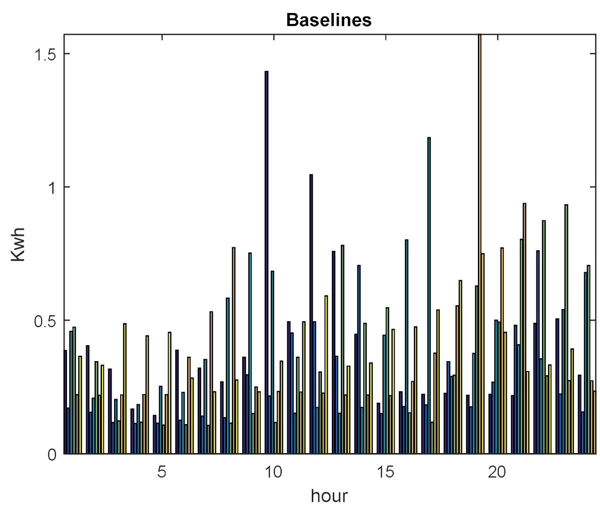


Figure 18: The hourly baseline consumption of the 6 flats of the building.

We set the heat transfer parameter of the building *a*=0.054 and the efficiency parameter of the heat radiators of the houses (flats) to be *b*=4. We assume that the indoor temperature at the beginning of the time slot of interest is T^{in}=22 Celsius for all houses and that the outdoor temperature is T^{out}=2 Celsius. We set the comfort constraints for all users to be the same, specifically the minimum tolerable temperature to be T^{min}=21 Celsius and the maximum permissible temperature to be T^{max}=25 Celsius. The time slot of interest for flexibility provision is assumed to be *τ*=13.The cost of 1 KWh is assumed to be 0.1 EUR.

We first consider the case where there is no reward for flexibility provision and according to the user's utility functions there is no utility loss associated with the indoor temperature drop, as long as the comfort constraints are not violated.

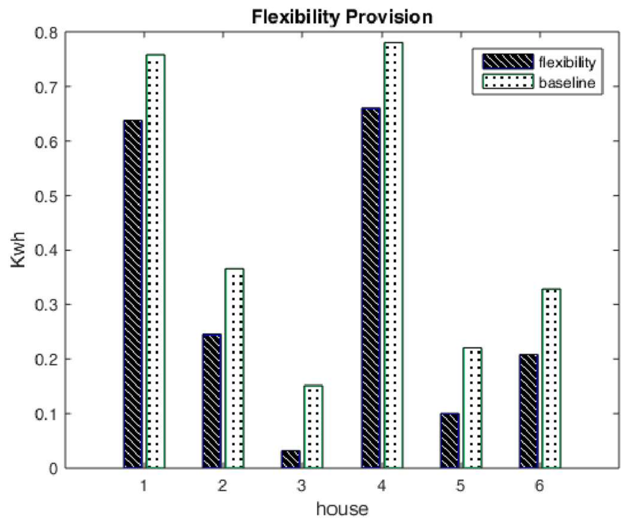


Figure 19: Flexibility provision when no rewards and no utility loss.

As it can be observed in Figure 19, when no user utility loss arises due to indoor temperature drop, users are still motivated to provide as much flexibility is possible within the comfort constraints due to savings in their bill.

Next, we consider that there does apply user utility loss by deterioration of the indoor temperature. In particular, we assume that the user utility function is the square root of the indoor temperature, which is a concave function. The flexibility provided in this case is depicted in Figure 20. Evidently, users offer lower amounts of flexibility when their dissatisfaction from indoor temperature drop is considered. Nevertheless, due to savings in the bill, some flexibility can still be attained, despite the lack of additional monetary rewards as flexibility incentives.

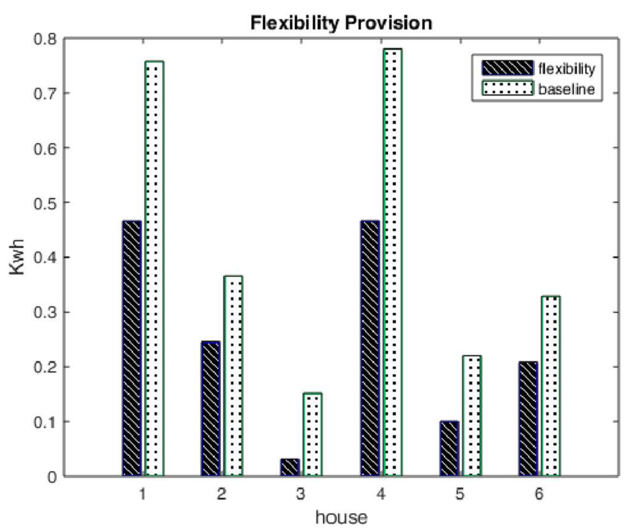


Figure 20: Flexibility provision when user utility loss is considered but no rewards.

Next, flexibility rewards are provided to the users to compensate them for their user utility loss within a total budget of B=10 EUR per flexibility event. In this case, the flexibility provided by the users (see Figure 21) increases almost to the same level with the case where no user utility loss is considered. An optimal reward r=0.5 EUR per KWh is calculated per energy flexibility unit, which results in the rewards per house illustrated in Figure 22.

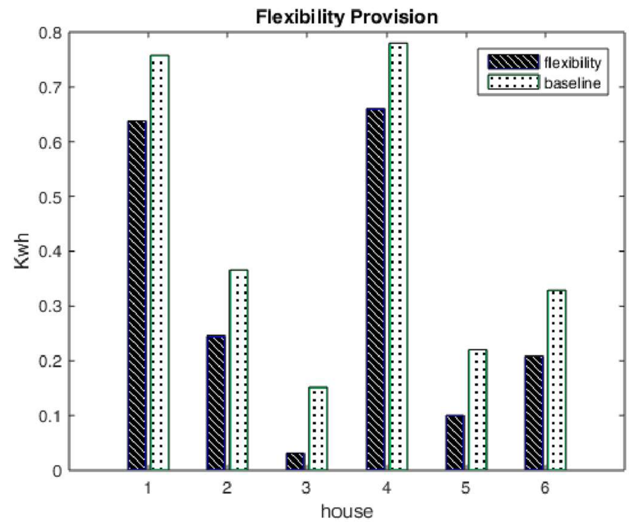


Figure 21: Flexibility provision with user utility loss and flexibility rewards.

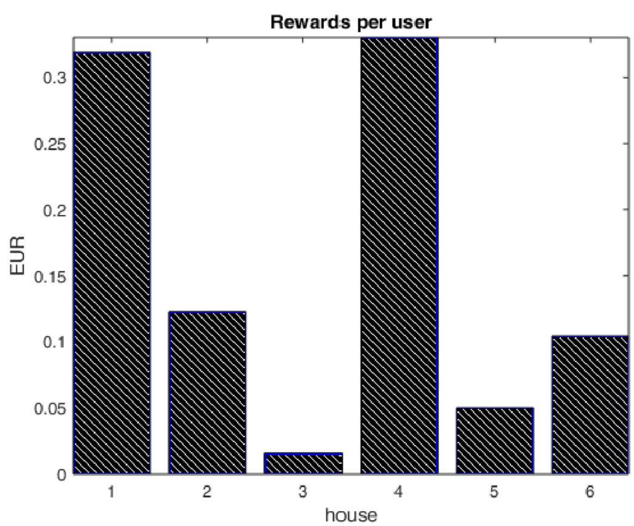


Figure 22: Rewards per house for flexibility provision.

Finally, we consider the case that user utility deterioration due to indoor temperature drop is considered, no flexibility rewards compensate it, but the price for total energy consumption are higher at the flexibility slot, namely they are equal to 0.4 EUR per KWh. The flexibility provision in this case is depicted in Figure 23. As shown therein, peak energy tariffs can have the same effect for the users as flexibility rewards.

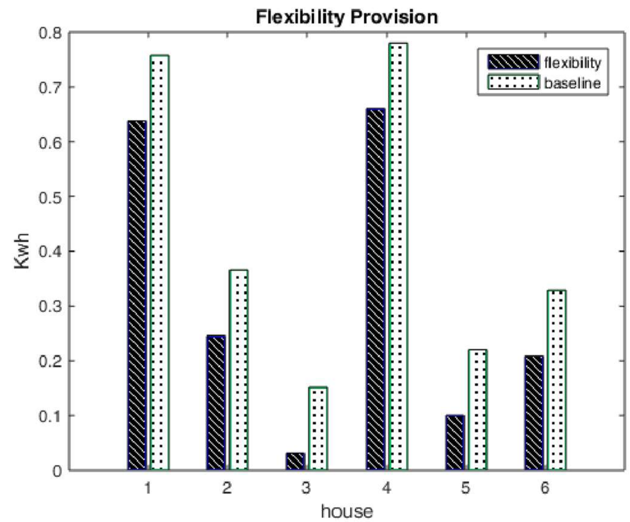


Figure 23: Flexibility provision when user utility loss is considered, no flexibility rewards, but peak tariff at the flexibility slot.

6.2 Shared Total Energy Bill and Multiple Flexibility Slots under Full Information

We consider a context similar to that of Section 6.1, however, the flexibility provision per house (apartment), starting at the time slot of interest τ, may span several time slots, i.e., hours in our case, until the end of the day, according to the interests and comfort constraints of the occupants of the house. Again, we consider total energy consumption per house. While the district heating is turned off during the flexibility event that starts at time slot τ, users may use electrical heating devices to compensate for the lost heat. $x^t_{n,0}$ expresses the total baseline energy consumption (electricity and district heating) of customer/house n at time slot t, while x^t_n denotes his energy flexibility at the same slot.

Then, the problem of the DR aggregator/flexibility manager in this context would be to maximize the total amount of energy flexibility that can be obtained by the users within the budget B for flexibility rewards. At each time slot t, with $0 \leq \tau \leq t \leq T$, the net benefit of each house owner n, given rewards r per energy flexibility unit, utility loss from indoor temperature drop, and bill savings from reducing energy consumption (assuming no rebound effects), should be non-negative. Also, for each time slot t, with $0 \leq \tau \leq t \leq T$, the comfort constraints of the users should not be violated. Specifically, the aggregator should solve the optimization problem below:

$$\boldsymbol{Maximize} \sum_{n \in N} \sum_{t=\tau}^{T} x_n^t \tag{23}$$

$$\boldsymbol{s.t.} \quad r \cdot \sum_{t=\tau}^{T} x_n^t - \sum_{t=\tau}^{\tau+S-1} \left(U_n\left(x_{n,0}^t\right) - U_n\left(x_{n,0}^t - x_n^t\right) \right) + c(\boldsymbol{x}_n) \geq 0, \; \forall\, n \in N \tag{24}$$

$$T_n^{min} \leq T_n^{in}(t) \leq T_n^{max}, \; \forall\, n \in N, \; t = \tau, \dots, T \tag{25}$$

$$r \cdot \sum_{n \in N} \sum_{t=\tau}^{T} x_n^t \leq B \tag{26}$$

$$T_n^{in}(t) = (1-a)^{t-\tau} T_n^{in}(\tau-1) + \sum_{tt=\tau}^{t} (1-a)^{t-\tau} b \cdot T_n^{out}(tt) + \sum_{tt=\tau}^{t} (1-b)^{t-\tau} \lambda \cdot \left(x_{n,0}^t - x_n^t\right) \tag{27}$$

The indoor temperature for each house n for time slots $t \geq \tau$ is derived from (Li, Chen & Low, 2011) given different outdoor temperatures for these time slots and the initial indoor temperature at time slot τ-1.

6.2.1 Numerical Evaluation

We consider again the REDD dataset of 6 houses from (Kotler & Johnson, 2011). We assume that the user utility function for a house owner n is the square root of the indoor temperature of his house. We assume a total budget for flexibility rewards B=10 EUR. We consider the case of user utility deterioration due to indoor temperature drop, which is compensated with a reward r per flexibility unit provided. The time slot of interest is considered to be τ=13. Then, the energy flexibility provided per house of the building from time slots $\tau \leq t \leq T$ is illustrated in Figure 24. As shown therein, house 2 cannot provide any flexibility, while other houses split their energy flexibility provision in multiple slots. This was expected by the users, in order to keep indoor temperature drops minimal per time slot, while overall benefit from flexibility rewards.

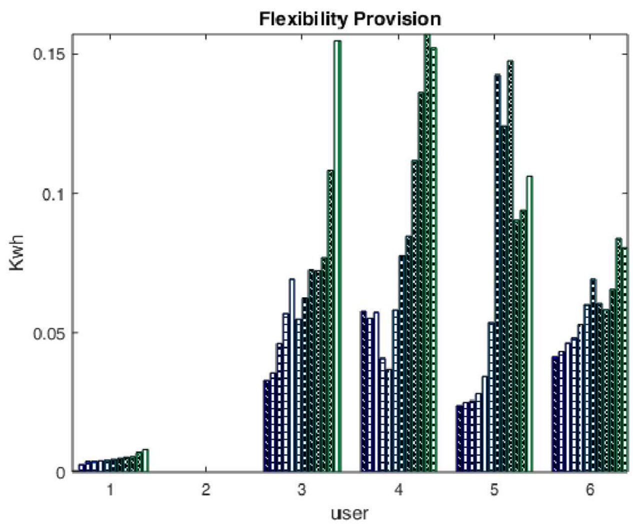


Figure 24: Flexibility provision for multiple slots given user utility drop and flexibility rewards.

The optimal reward per energy flexibility unit was found to be r=1.14 EUR per KWh., while the total flexibility rewards per house are illustrated in Figure 25.

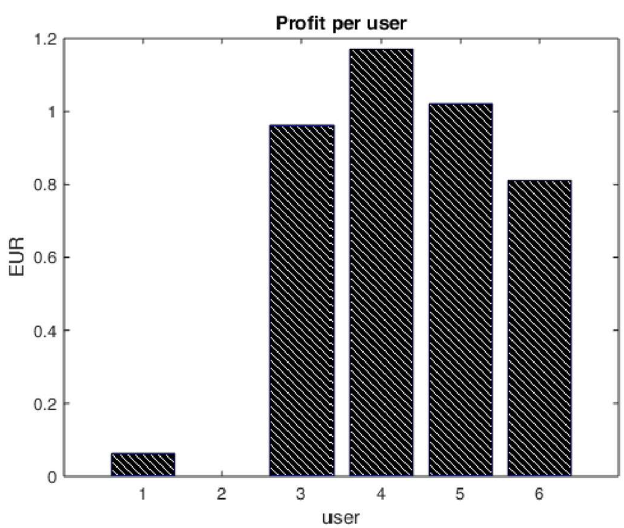


Figure 25: Total flexibility rewards per user over multiple time slots.

6.3 Thermal Energy Flexibility

The previous models have considered total energy consumption in energy flexibility provision. However, in the absence of smart meters for the individual houses (apartments) of the building, energy flexibility provision by the different houses cannot be validated. However, the previous models are still useful to investigate user incentives and behavior when such a flexibility management mechanism is employed in practical settings. In the present model, we consider energy flexibility from district heating energy only, i.e., turning it off for some time exploiting the thermal capacity and the insulation of the building, without considering the electricity consumption of the residents of the building. The district heating bill is shared evenly over the N apartments of the building. When turning off the district heating of a building, we assume that each apartment of the building equally contributes the same amount *x* to the thermal energy flexibility of the building per time slot. Comfort constraints for the house owner *n* of the building dictate that the temperature is not allowed to drop below T_n^{min} or rise above T_n^{max}. We assume that the flexibility event for the building terminates when one of these constraints is about to be violated. This mechanism could be easily implemented by means of user feedback on their comfort, which would warn about such a violation. There may be a loss in user utility $U_n(.)$ for occupants of flat *n* associated with the indoor temperature drop. Moreover, there may be a reward *r* for the occupants of each house per energy flexibility unit provided by them within a total budget *B*. The objective of the DR aggregator / flexibility manager in this context is to maximize the total flexibility that can be obtained by the building.Since,the flexibility per apartment and per slot is fixed, this amounts to maximizing the duration *S* of the flexibility event, as follows:

$$\boldsymbol{Maximize}\ N\cdot\ x\ \cdot S \tag{28}$$

$$\boldsymbol{s.t.}\ \ r\ \cdot x\cdot\ S-\sum\nolimits_{t=\tau}^{\tau+S-1}\Big(U_n\big(x_{0,t}\big)-U_n\big(x_{0,t}-x\big)\Big)+c(S\,x)/N\geq 0,\ \forall\, n\ \in N \tag{29}$$

$$T_n^{min}\leq T_n^{in}(t)\leq T_n^{max},\ \forall\, n\ \in N,\ t=\tau,\dots,\tau+S-1 \tag{30}$$

$$N\ \cdot r\ \cdot x\ \cdot S\leq B \tag{31}$$

Deriving from (Li, Chen & Low, 2011), turning off the district heating at time slot *τ*, the indoor temperature $T_n^{in}(.)$ evolves over time slot *t*, as follows:

$$T_n^{in}(t)=(1-a)^{t-\tau}T_n^{in}(\tau-1)+\sum\nolimits_{tt=\tau}^{t}(1-a)^{t-\tau}\beta\cdot T_n^{out}(\,tt) \tag{32}$$

6.3.1 Numerical Evaluation

We assume the indoor temperature of the building before the flexibility event to be 24 degrees Celsius and the outdoor temperature to be 0 degrees Celsius. The indoor temperature as function of the duration of the flexibility event and the heat transfer parameter of the building is depicted in Figure 26 below.

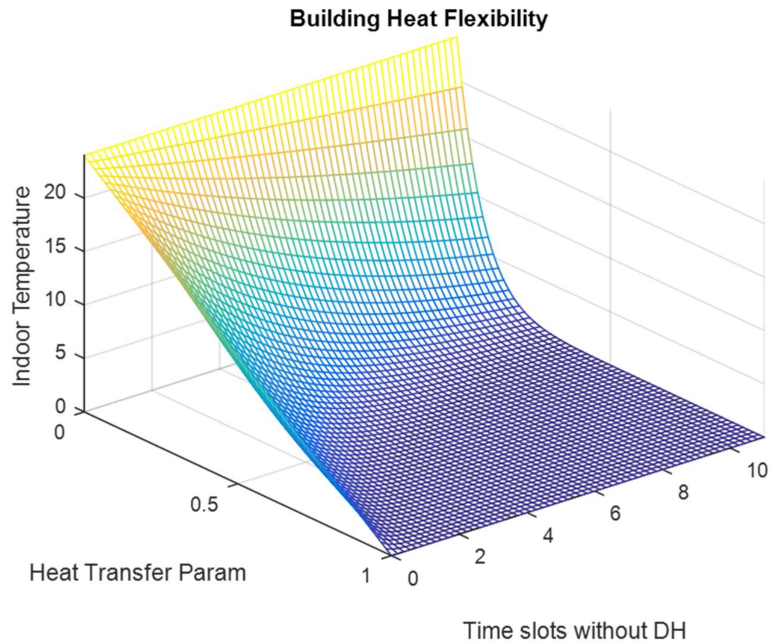


Figure 26: The thermal energy flexibility potential of a building w.r.t. its heat exchange parameter.

We assume that the user utility function $U_n(.)$ of the owner of flat n equals to the square root of the indoor temperature in his flat. We run the optimization model (28)-(31) for finding the optimal rewards for maximizing the duration S for different heat exchange parameters of the building. As depicted in Figure 27, the lower the heat exchange parameter α of the building, the lower the incentives needed and the higher the duration of flexibility provision and vice versa.

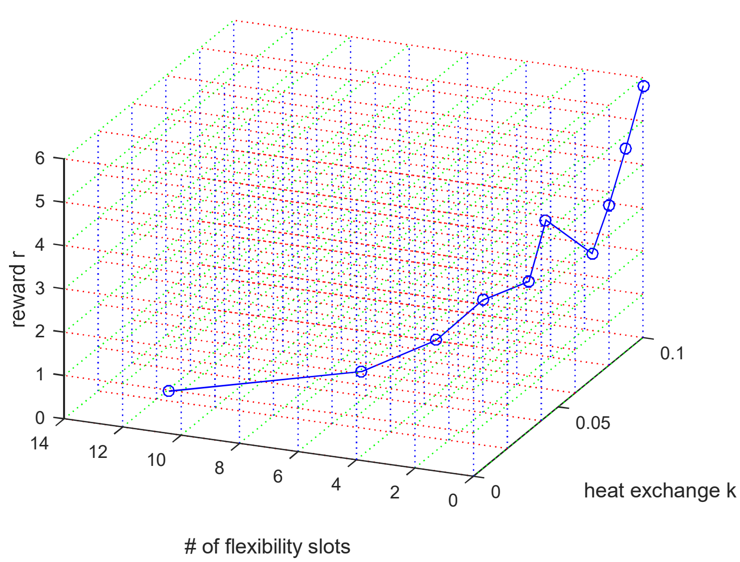


Figure 27: Optimal rewards for maximizing thermal energy flexibility in the building for different heat exchange parameters.

6.4 The Public Goods Context

So far, we have assumed that users always enjoy some benefit when some flexibility is attained. Next, we study a case where users belonging to a certain group participate in a DR event for aggregating a *specific* amount of flexibility. If this flexibility objective is indeed achieved then a specific reward (or a bill discount) is shared among the users of the group. Otherwise, the participating users endure only costs. To this end, we assume that users actually participating in DR exert a *costly effort*. On the other hand, non-participating users do not endure any costs, while at the same time, they may enjoy rewards if the flexibility objective is met, grace to the flexibility offered by the others.

Thus, flexibility rewards represent a *public good* for the group of users. This setting is similar to a number of interesting real-world cases where collective action is needed, while observability of *individual* contributions is *not* supported, e.g.:

- An office building where employees are asked to participate in a flexibility event by conserving energy in a particular time period. If they collectively succeed in the flexibility objective, then they all share some bonus in their salary.
- A community of users that a district heating company notifies to lower the set-point temperature at their premises in particular time periods, in exchange for bill discounts. If no related telemetry equipment is considered at the customer premises, then individual participation to the flexibility event cannot be verified.
- Building occupants that share the bill for some common energy services, e.g., heating, lighting, lift, and may offer building flexibility. Reducing energy consumption for these services in particular time periods, necessitates collective effort.

6.4.1 The Model

Consider that an overall energy flexibility objective X has to be achieved by a group $\mathcal{N}$ of users at a particular time slot of interest τ. We assume that each participating user provides flexibility x. This can either be taken as fixed (for simplicity reasons), or as being some average measure of the flexibility offered by all users. Then, at least $\lceil X/x \rceil$ users have to participate, so that the aimed energy flexibility to be achieved. In the successful case, a total reward $R=r \cdot X$ is shared among the users, where r is the reward per flexibility unit. Each participating user $n \in \mathcal{N}$ endures a user utility loss $\Delta U_n = U_n(x_{n,0})-U_n(x_{n,0} - x)$, where $U_n(\cdot)$ is a personalized concave user utility function for energy consumption and $x_{n,0}$ is the baseline energy consumption of user n. This loss of utility corresponds to the costly effort referred to above. There is uncertainty involved in achieving the collective energy flexibility objective, which depends on the likelihood of individual users participating in the flexibility event. We denote with p_n the probability that user n participates in flexibility provision. Then, the probability that the flexibility goal is met given that user n participates is given by:

$$Pr(OK \mid n \text{ participates}) = \sum_{i=\lceil X/x \rceil -1}^{N-1} \; \sum_{\forall\, \mathcal{S} \subseteq \mathcal{N}-\{n\}, |\mathcal{S}|=i} \underbrace{p_k \cdot \ldots p_m}_{k,m \,\in\, \mathcal{S}} \cdot \underbrace{(1-p_u) \cdot \ldots (1-p_v)}_{u,v \,\in\, \mathcal{N}-\{n\}/\mathcal{S}} \quad (33)$$

Thus, the public good will be created if at least $\lceil X/x \rceil -1$ users, other than user n, participate in the flexibility event. The probability that the flexibility goal is met given that user *n does not* participate is given by:

$$Pr(OK \mid n \text{ does not participate}) = \sum_{i=\lceil X/x \rceil}^{N-1} \; \sum_{\forall\, \mathcal{S} \subseteq \mathcal{N}-\{n\}, |\mathcal{S}|=i} \underbrace{p_k \cdot \ldots p_m}_{k,m \,\in\, \mathcal{S}} \cdot \underbrace{(1-p_u) \cdot \ldots (1-p_v)}_{u,v \,\in\, \mathcal{N}-\{n\}/\mathcal{S}} \quad (34)$$

Therefore, in this case, the public good will be created if at least $\lceil X/x \rceil$ users, other than user n, participate in the flexibility event.

6.4.2 Equilibrium Analysis

We consider the context as a *game* among users where a user has two pure strategies to play against all other users, i.e., participate or not in the flexibility provision. Therefore, the probability p_n that each user n participates in the flexibility provision determines his ***mixed strategy*** according to which he chooses to participate or not. The expected payoff of a user n, when playing participate, is given by:

$$\Pi_n^c(p_n, p_{-n}) = Pr(OK \mid n \text{ participates}) \cdot (\Delta U_n + R/N) + (1 - Pr(OK \mid n \text{ participates})) \cdot \Delta U_n = Pr(OK \mid n \text{ participates}) \cdot R/N + \Delta U_n \quad (35)$$

where p_{-n} denotes the mixed strategies of all users other than n. Therefore, the expected payoff of the user equals the probability that the public good will be created times the share of rewards for the user minus the user utility loss, which is always incurred by a user participating in DR. The expected payoff of a user n, when playing not participate, is given by:

$$\Pi_n^{nc}(p_n, p_{-n}) = Pr(OK \mid n \text{ does not participate}) \cdot R/N \quad (36)$$

Then, at mixed strategy Nash equilibrium, each user $n \in \mathcal{N}$ should select his mixed strategy p_n, so that he is indifferent at the equilibrium between playing participate or not, i.e.,

$$\Pi_n^c(p_n, p_{-n}) = \Pi_n^{nc}(p_n, p_{-n}) \quad (37)$$

One has to realize that this problem can be solved for an arbitrary number of users, because for each user n with unknown variable p_n there is one equation, hence overall we have a system of N equations for N unknown variables.

6.4.2.1 Homogeneous Case

A simplified instance of the aforementioned problem that does not involve solving a system of equations is the case where all users can be considered homogeneous, i.e., with the same user utility function. Therefore, due to symmetry, in the mixed strategy Nash equilibrium all users will be employing the same probability for selecting to participate. Hence, dropping indices, the probability of the user to participate in flexibility provision is simply denoted as p, while his user utility loss is denoted by ΔU. The respective expected payoffs $\Pi^c(p)$, $\Pi^{nc}(p)$ for the strategies participate or not participate are given by:

$$\begin{aligned}\Pi^c(p) &= Pr(OK \mid n \text{ participates}) \cdot R/N + \Delta U \\ &= \sum_{i=\lceil X/x \rceil - 1}^{N-1} \binom{N-1}{i} p^i (1-p)^{N-1-i} \cdot \frac{R}{N} + \Delta U\end{aligned} \quad (38)$$

$$\begin{aligned}\Pi^{nc}(p) &= Pr(OK \mid n \text{ does not participate}) \cdot R/N + \Delta U \\ &= \sum_{i=\lceil X/x \rceil}^{N-1} \binom{N-1}{i} p^i (1-p)^{N-1-i} \cdot \frac{R}{N}\end{aligned} \quad (39)$$

At equilibrium, there should hold $\Pi^c(p) = \Pi^{nc}(p)$.Thus, one can find the mixed equilibrium strategy p of each user; that is, his probability to participate in flexibility provision.

6.4.3 Numerical Evaluation

We consider the homogeneous case, where all users (i.e. flat owners) have the same user utility function equal to the square root of their energy consumption. We assume that the total amount of requested energy flexibility is X=1 KWh at the time slot of interest, while the baseline energy consumption by each user n is $x_{n,0}$=1 KWh at the same time slot. We vary the number N of users from 10 to 15. We vary the individual energy flexibility contribution x from 0.1KWh to 0.2KWh with step 0.05KWh. We also vary the reward r to be shared among users (leading to a total reward $R=r{\cdot}X$ when the flexibility objective is met) from 20 to 25 EUR with step 1. In these ranges, we seek to find all feasible solutions for the participation probability p and the individual flexibility contribution x at equilibrium. As illustrated in Figure 28, the participation probability for each user in the flexibility event drops with the number of users, increases with the amount of total rewards $R=r \cdot X$, and drops with higher user utility loss (i.e., higher individual flexibility contribution x).

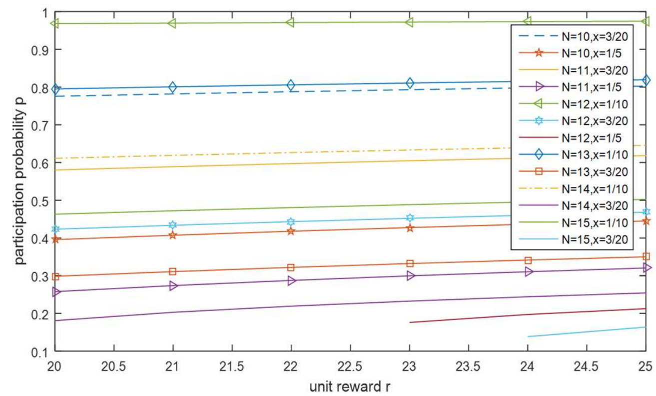


Figure 28: Equilibrium solutions for the participation probability of each user to the flexibility event w.r.t. the reward *r* per flexibility unit, the total requested flexibility *X* and the community size *N*.

Moreover, at each equilibrium point, we investigate the relationship between the participation probability p of a user to the flexibility event with the amount *R* of total rewards for flexibility provision. As illustrated in Figure 29, we consistently found at all equilibrium points that the higher the total flexibility rewards, the higher the participation probability of the users to the flexibility event, as expected. Also, notice again that the participation probability of the users drops with the higher individual flexibility contribution.

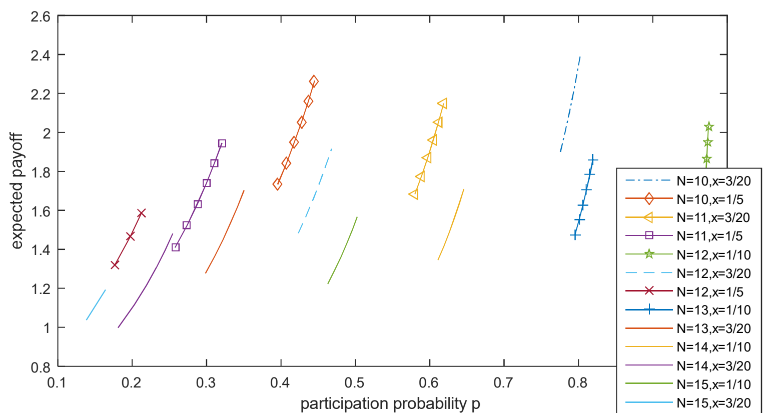


Figure 29: Higher flexibility rewards increase the user participation probability to the flexibility event and give higher expected payoffs for the users at equilibrium.

6.5 Conclusions

To summarize, we defined and investigated a variety of models and optimization frameworks for the Finnish pilot site. Specifically:

- We defined a model for one time slot for total energy flexibility provision to investigate individual incentives for counteracting turning off district heating by means of increasing electricity consumption. This model may accommodate user utility loss, flexibility rewards or peak energy tariffs and user comfort constraints at the time slot of interest.
- We considered the previous model, but in a longer time horizon, to investigate incentives for energy flexibility provision that start at a time slot of interest and continue for the rest of the day.

- We defined another model with fixed thermal flexibility contributions per apartment of a building per time slot due to turning off district heating. This model is complementary to the ones for energy flexibility provision, and investigates the upper bound on the duration of the flexibility event in a building when flexibility rewards and user comfort constraints are in place.
- We also defined a model where flat owners (i.e. users) contribute thermal energy flexibility towards a common aggregate objective, e.g., a certain value of the total energy flexibility, or equivalently of the reduction in the building heating bill. Users are rewarded only if this objective is met. This setting resembles a public goods model.

All models consistently found that flexibility aggregation can be effective when appropriate incentives are provided to the users, even if user-utility deterioration associated to indoor temperature drop in the apartments of the users is considered. All models are applicable for the provision of DR incentives in practical cases of buildings such as that of the Finnish pilot. The choice of the appropriate model depends on the specificities of the case where DR is applied in such a setting.

7. Conclusion

This deliverable completes the reporting on the work carried out by Task 5.3 – *Incentive mechanisms and consumer engagement*, and particularly by documenting the work accomplished by this Task, following submission of D5.3. To this end, a tailored approach was developed and finalized for each one of the pilots, due to their inherent differences. Moreover, 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 concrete propositions for their combination with non-economic incentive mechanisms.

In particular, for the Greek pilot, a mutually beneficial bilateral trading scheme is introduced between a RES and a DR aggregator. The objective of this scheme is to internally offset real-time energy imbalances before resorting to the flexibility market. It is considered that the DR aggregator manages the energy demand of users, and thus the actual provision of flexibility, subject to their offered monetary incentives and to their uncertainty in participating in DR events. It is taken that the RES aggregator faces penalties according to dual pricing for positive or negative imbalances. To this end, we develop an optimization framework to achieve the required flexibility, while addressing the trade-off between maximizing the profit of RES and DR aggregators and appropriately incentivizing the users. By using appropriate parameterization of the solution, the achievable revenue for the imbalance offsetting can be shared between the RES and the DR aggregators, while keeping users satisfied. Furthermore, the integration of the incentives' component in the iFLEX assistant is presented. Also, various considerations for its effective implementation are discussed. In particular, these involve new studies on the discovery (i.e. learning) of the model of the users during the initial stage of the pilot. In that stage, incentives are provided using neither an optimization algorithm nor an explanation of the data exchanges between the incentives' component and the rest of the iFLEX assistant. As a final remark, it should be reminded that the rewards (incentives) calculated by means of the model of the Greek pilot are *not* "paid" directly to the users. Instead, users participate in a *lottery* (e.g. per month), in which each user's probability to win is proportional to his total rewards accumulated in this period. Moreover, the value of the prize awarded equals the sum of these total rewards across all users.

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 already specified and investigated in D5.3; this includes rewards, lotteries, and 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. Moreover, 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. Also, 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. In this deliverable, a complementary formulation was developed that includes optimal choice of flexibility at the level of individual appliance. This results in a suboptimal, yet privacy-friendly, approach; namely, to run first the distributed iterative algorithm between the aggregator and the users to estimate the total per user flexibility, and then to derive (for each user) the most proximal combination of flexible assets the user premises that can provide this flexibility.

As for the Finnish pilot, the building's heating system is taken to be the source of flexibility. In particular, flexibility emerges due to the thermal mass of the building, which can be used to store energy. Flexibility management is based on the following assumption: 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 already specified and investigated in D5.3; 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, thermal model of the building, and budget constraints incentives. Numerical assessment of all models consistently confirmed that flexibility aggregation can be effective, when appropriate incentives are provided to the users, in the case where user-utility deterioration associated to drop of the indoor temperature in the apartments is considered and thus has to be compensated.

These investigations are complemented by Chapter 3 of the present deliverable. This contains the statistical analysis of the responses received to the user questionnaire, shedding light on users' main behavioral traits that can be combined with monetary incentives in order to enhance their effectiveness. One of the main lessons learned by this analysis is as follows: respondents believe that rewards and/or peer pressure can indeed motivate consumers to provide energy flexibility. Moreover, we found that consumers indeed have indeed the ability to offer energy flexibility, as summarized by their knowledge and their capability, as well as that there is an opportunity dimension related to the user intentions to exert flexible energy behavior. This dimension involves the energy flexibility visualization, the automated energy flexibility or the energy flexibility advice and the external energy flexibility control, all of which are in-line with the iFLEX approach!

Project iFLEX is already in its final stage, where pilots will be completed and their outcomes will be assessed, thus offering a valuable opportunity to evaluate the theoretically sound incentive mechanisms developed by WP5 from the viewpoint of their application in practice.

8. List of figures and tables

8.1 Figures

8.2 Tables

9. References

(Sharma et al, 2021)	S. Sharma, A. Verma and B. K. Panigrahi, "Robustly Coordinated Distributed Voltage Control Through Residential Demand Response Under Multiple Uncertainties," in *IEEE Transactions on Industry Applications*, vol. 57, no. 4, pp. 4042-4058, July-Aug. 2021, doi: 10.1109/TIA.2021.3079135.
(Yuan et al, 2023)	Z. -P. Yuan, P. Li, Z. -L. Li and J. Xia, "Data-Driven Risk-Adjusted Robust Energy Management for Microgrids Integrating Demand Response Aggregator and Renewable Energies," in IEEE Transactions on Smart Grid, vol. 14, no. 1, pp. 365-377, Jan. 2023, doi: 10.1109/TSG.2022.3193226.
(Du et al, 2018)	Y. F. Du, L. Jiang, Y. Li and Q. Wu, "A Robust Optimization Approach for Demand Side Scheduling Considering Uncertainty of Manually Operated Appliances," in IEEE Transactions on Smart Grid, vol. 9, no. 2, pp. 743-755, March 2018, doi: 10.1109/TSG.2016.2564159.
(Paridari, 2016)	K. Paridari, A. Parisio, H. Sandberg and K. H. Johansson, "Robust Scheduling of Smart Appliances in Active Apartments With User Behavior Uncertainty," in IEEE Transactions on Automation Science and Engineering, vol. 13, no. 1, pp. 247-259, Jan. 2016, doi: 10.1109/TASE.2015.2497300.
(Pearson, 1895)	K. Pearson (1895), "Notes on regression and inheritance in the case of two parents". Proceedings of the Royal Society of London. 58: 240–242.
(Vahid et al, 2021)	M. Vahid-Ghavidel et al., "Novel Hybrid Stochastic-Robust Optimal Trading Strategy for a Demand Response Aggregator in the Wholesale Electricity Market," in IEEE Transactions on Industry Applications, vol. 57, no. 5, pp. 5488-5498, Sept.-Oct. 2021, doi: 10.1109/TIA.2021.3098500.
(D7.6, 2023)	HORIZON 2020 iFLEX project, "D7.6 Small-scale pilot deployment and validation," 31 May 2023. [Online]. Available: https://www.iflex-project.eu/download/d7-6-small-scale-pilot-deployment-and-validation/.
(Carreiro et al, 2017)	A. M. Carreiro, H.M. Jorge and C.H. Antunes, "Energy management systems aggregators: A literature survey," Renewable and Sustainable Energy Reviews, vol. 73, pp. 1160-1172, June 2017.
(Algarvio et al, 2023)	H. Algarvio and F. Lopes, "Bilateral Contracting and Price-Based Demand Response in Multi-Agent Electricity Markets: A Study on Time-of-Use Tariffs," Energies, vol. 16, no. 2, p. 645, January 2023.
(Mahmoudi et al, 2015)	N. Mahmoudi, T.K. Saha and M. Eghbal "Wind Power Offering Strategy in Day-Ahead Markets: Employing Demand Response in a Two-Stage Plan," IEEE Transactions on Power Systems, vol. 30, no. 4, pp. 1888-1896, July 2015.
(Cheung & Yip, 2005)	M. W.L. Cheung, P. S.F. Yip. Theta Reliability, Editor(s): Kimberly Kempf-Leonard, Encyclopedia of Social Measurement, Elsevier, 2005, pp. 791-796, ISBN 9780123693983.
(Nordic Model, 2019)	Nordic Balancing Model, "Analysing different alternatives for single pricing model implementation," 10 May 2019. [Online]. Available: https://nordicbalancingmodel.net/wp-content/uploads/2019/10/Single-pricing-model-timeline-report-clean-190910-For-publication.pdf.
(Krasopoulos, Papaioannou & Stamoulis 2022)	C. T. Krasopoulos, T. G. Papaioannou and G. D. Stamoulis, "Flexibility Management for Residential Users Under Participation Uncertainty," 2022 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Singapore, Singapore, 2022, pp. 405-411, doi: 10.1109/SmartGridComm52983.2022.9961041.

(D5.3, 2011)	HORIZON 2020 iFLEX project, "D5.3 iFLEX consumer engagement and incentive mechanisms," 3 October 2022. [Online]. Available: https://www.iflex-project.eu/download/d5-3-iflex-consumer-engagement-and-incentive-mechanisms/.
(Minou et al, 2011)	M. Minou, G. D. Stamoulis, G. Thanos and V. Chandan, "Incentives and targeting policies for automated demand response contracts," *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Miami, FL, USA, 2015, pp. 557-562, doi: 10.1109/SmartGridComm.2015.7436359.
(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.
(Papaioannou & Stamoulis, 2022)	T. G. Papaioannou and G. D. Stamoulis, "An Optimization Framework for Effective Flexibility Management for Prosumers," 2022 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Singapore, Singapore, 2022, pp. 103-109, doi: 10.1109/SmartGridComm52983.2022.9961040.
(Tondello et al., 2016)	Tondello, Gustavo & Wehbe, Rina & Diamond, Lisa & Busch, Marc & Marczewski, Andrzej & Nacke, Lennart. (2016). The Gamification User Types Hexad Scale. 10.1145/2967934.2968082.
(Stern et al., 1999)	Stern, P., Dietz, T., Abel, T., Guagnano, G., & Kalof, L. (1999). A value belief-norm theory of support for social movements: The case of environmentalism. Human Ecology Review, 6, 81–97
(Frederiks, Stenner & Hobman, 2015)	E. R. Frederiks, K. Stenner and E. V. Hobman. The Socio-Demographic and Psychological Predictors of Residential Energy Consumption: A Comprehensive Review. Energies, vol. 8, MDPI, pp. 573-609, 2015.
(De Young, 2000)	De Young, R. Expanding and evaluating motives for environmentally responsible behavior. J. Soc. Issues 2000, 56, 509–526.
(Kollmuss & Agyeman, 2002)	Kollmuss, A.; Agyeman, J. Mind the gap: Why do people act environmentally and what are the barriers to pro-environmental behavior? Environ. Educ. Res. 2002, 8, 239–260.
(Ajzen & Fishbein, 1980)	Ajzen, I. and Fishbein, M. (1980) Understanding Attitudes and Predicting Social Behavior, Prentice Hall Inc., Englewood Cliffs, NY.
(Kollmuss & Agyeman, 2002)	Kollmuss, A.; Agyeman, J. Mind the gap: Why do people act environmentally and what are the barriers to pro-environmental behavior? Environ. Educ. Res. 2002, 8, 239–260.
(Abrahamse & Steg, 2009)	Abrahamse, W.; Steg, L. How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings? J. Econ. Psychol. 2009, 30, 711–720.
(Abrahamse & Steg, 2011)	Abrahamse, W.; Steg, L. Factors related to household energy use and intention to reduce it: The role of psychological and socio-demographic variables. Hum. Ecol. Rev. 2011, 18, 30–40.