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Optimisation strategies for DR report [M18]

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DR-RISE

EXECUTIVE SUMMARY

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Executive Summary

Deliverable D4.3 - Optimisation strategies for DR report, provides a comprehensive analysis of the optimisation strategies developed in task T4.2 of the DR-RISE project. The main goal of this task is to develop advanced optimisation strategies for demand response, focusing on the design and integration of two pivotal modules comprising the architecture: User Smart Node (USN) and Aggregator Smart Node (ASN).

The deliverable begins by defining the objectives and scope of the optimisation strategies, laying out the foundational principles of demand response solutions. This section establishes the context for the approach introduced in the subsequent chapters. A general overview of each module's role within the system, including their inputs, outputs and frameworks utilised is presented in Chapter 2. The interconnections between the USN and ASN modules are also described in this section, highlighting how they work synergistically to improve the efficiency of the system.

Chapter 3 dives into the specifics of the USN optimisation, starting with an overall approach before detailing the Model Predictive Control (MPC) framework. It explores how MPC is used to optimise energy dispatch within a 24-hour forecast horizon, aiming at minimising energy costs through Price-Based Demand Response (PBDR). This involves the integration of forecasts related to energy consumption, price, feed-in tariffs and photovoltaic production (if applicable). The chapter also discusses how system constraints and demand response strategies are applied to ensure optimal performance. This exploration demonstrates the effectiveness of integrating advanced predictive tools in managing resources efficiently. The utilisation of PBDR within this context not only optimises costs but also aligns energy usage with market dynamics, environmental considerations, and user preferences.

On the other hand, the optimisation process for the ASN is covered in Chapter 4. It details the use of a Genetic Algorithm (GA) to effectively distribute flexibility and manage user contributions. The description begins with an overview of the genetic algorithm, including how the fitness function is designed and the overall strategy for its application. The ASN's role in making offers to the energy market during periods of supply and demand imbalance is explicitly detailed. Following the market acceptance, the GA is employed to distribute flexibility among users efficiently, taking into account their potential reduction capabilities. Moreover, the methodology for calculating baseline consumption is described, which is paramount for determining incentives under Incentive-Based Demand Response (IBDR), ensuring users receive appropriate rewards for their energy savings. The exploration of the GA highlights its effectiveness in managing and distributing user contributions efficiently, emphasising the ASN's pivotal role in dynamic market conditions and its impact on IBDR.

Practical examples of both USN and ASN optimisations are presented in Chapter 5, showing their execution and discussing the outcomes to evaluate the effectiveness of the implemented strategies, demonstrating the benefits of the developed optimisation strategies. These examples not only validate the theoretical models but also illustrate the scalability and flexibility of the optimisation strategies across different operational scenarios, as well as the substantial improvements in energy management and cost reduction.

Finally, Chapters 6 and 7 outline the directions for further development and potential research avenues. They synthesise the findings and highlight the value added by the optimisation strategies to the goals of the project, underlining the significant potential for refining these strategies to meet specific user needs and enhance overall energy management.

With the foundational strategies now established, the focus will shift towards refining these techniques and adapting them to meet specific user needs. This deliverable lays the groundwork for future enhancements, ensuring continued improvements in energy management and efficiency across the board.

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Abbreviations

List of abbreviations	
AI	Artificial Intelligence
ASN	Aggregator Smart Node
BEMS	Building Management Systems
BESS	Battery Energy Storage System
CMP	Capacity Market Program
DLC	Direct Load Control
DR	Demand Response
ESS	Energy Storage System
EV	Electric Vehicle
GA	Genetic Algorithm
HEMS	Home Energy Management System
IBDR	Incentive-Based Demand Response
KP	Knapsack Problem
MILP	Mixed Integer Linear Programming
MIQP	Mixed Integer Quadratic Programming
MLD	Mixed Logical Dynamical
MLS	Manual Load Shifting
MPC	Model Predictive Control
PBDR	Price-Based Demand Response
PV	Photovoltaic
RES	Renewable Energy Resources
SOC	State of Charge
SSP	Subset Sum Problem
TSO	Transmission System Operator
USN	User Smart Node

1 Introduction

A **Home Energy Management System (HEMS)** comprises hardware and software that aim to manage energy use in residential environments efficiently. This concept is related to Building Management Systems (BEMS), principally differing in their target group; the BEMS is more focused on business environments, while HEMS applies to the domestic sector. The optimisation of HEMS has recently gained significant attention since domestic owners are required to reduce their energy consumption due to economic and environmental issues. Moreover, due to the recent expansion of **Renewable Energy Resources (RES) and Energy Storage Systems (ESS)**, besides dealing with energy consumption, modern HEMS are required to interact with generation and storage assets, which require advanced control optimisation techniques to balance end-users' comfort with grid demands.

In addition, the intermittent nature of RES can compromise the grid's stability, for which **Demand Response (DR)** emerges as a promising solution to address supply-demand imbalances. DR allows users to adjust their energy consumption in reaction to price signals or incentives. As a result, this approach permits end-consumers to contribute to grid stability instead of the typical supply increases to handle demand.

The DR-RISE project introduces a multi-layer solution that optimises energy distribution while maintaining household comfort and enabling flexible DR programs. To this end, a two-layer solution is deployed to minimise the costs and reduce the impact of peak loads in multiple homes. Among the different frameworks available, this advanced control architecture is based on **Model Predictive Control (MPC)**, enabling HEMS to solve complex, multi-objective problems in real-time, adjusting to network requirements and subject to operational constraints and uncertainties.

1.1 Objective and scope

This deliverable, which is within WP4 of the DR-RISE project, provides a detailed overview of the optimisation modules. The project's objective is to implement DR in the residential sector to demonstrate the benefits of its adoption, not only for individual households but also for the entire energy system. As a result, introducing flexible measures adds another degree of complexity regarding energy management, requiring accurate and precise control strategies.

The scope of this report is structured to guide the reader through the different DR-RISE optimisation modules, initially providing an overview and going into more detail as the document progresses. It is organised as follows:

- **Section: Introduction** – This section provides an overview of the energy framework for demand response, highlighting the current status of different technologies, their advantages, and their challenges.
- **Section 2: Optimisation overview** – The control architecture and strategies implemented in the project's optimisation are outlined in this section. The optimisation comprises two distinct modules: the User Smart Node (USN) and the Aggregator Smart Node (ASN).

- **Section 3: USN optimisation** – This section delves into the optimisation module applied at the household level to manage optimal energy dispatch, detailing the underlying model predictive control strategy.
- **Section 4: ASN optimisation** – This section describes the optimal management of demand response events through a genetic algorithm to provide energy flexibility and meet market needs.
- **Section 5: Results and discussion** –Execution examples of the different optimisation modules are presented and analysed in this section.
- **Section 6: Future work** – This section presents future lines of work to complete the project's optimisation module and outlines several possible ideas to explore.
- **Section 7: Conclusion** – The report concludes with this section, providing closing remarks on what has been achieved regarding DR-RISE's optimisation strategies.

1.2 Background

1.2.1 Demand response solutions

Whenever end-users adjust their typical consumption patterns or habits in reaction to market signals, they are said to be participating in demand response. The latter can be broadly classified into two main types: implicit (or price-based) and explicit (or incentive-based), represented in Figure 1 [1]. Implicit DR is characterised by providing end-users with time-varying electricity prices, encouraging them to shift their consumption to peak load periods when electricity prices are lower. Conversely, explicit DR involves the utility company instructing end-users to modify their consumption, offering financial incentives usually reflected on the monthly bill.

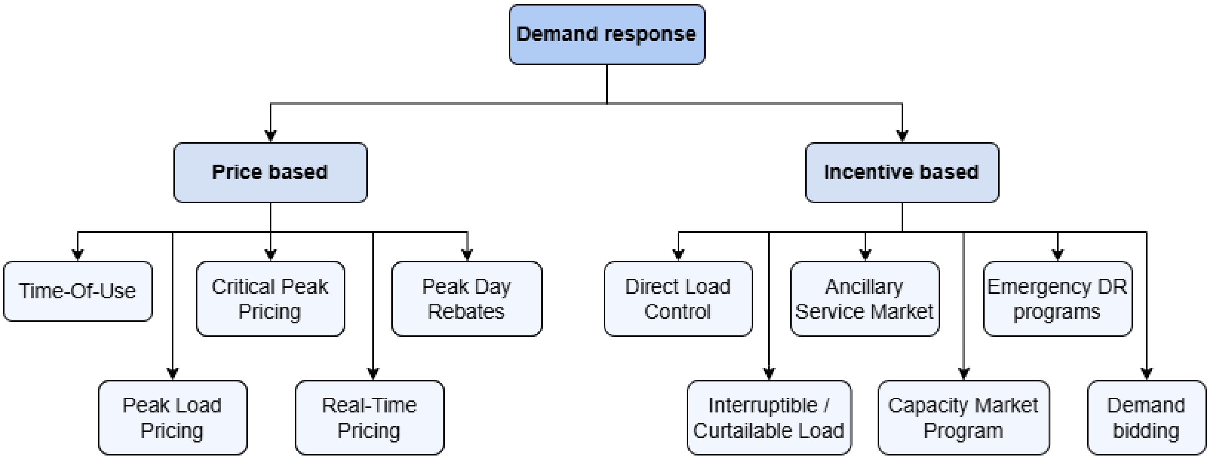

Figure 1. Classification of demand response programs

The DR-RISE project prioritises explicit DR strategies over implicit ones. End-users can opt for implicit DR solutions via their dynamic electricity tariff of choice. In this regard, the DR-RISE optimisation and solution are designed to seamlessly accommodate any dynamic tariff structure.

Keen to develop user-centred solutions, explicit DR seems to be a feasible option because it allows users to select the alternative that best suits their needs. Among all available explicit DR approaches, this project focuses on the following:

- **Direct Load Control (DLC)** is the most commonly used program in the residential sector, whenever implicit DR is available, and allows the utility company to remotely control and switch on/off the user's electrical assets to adapt the demand to the market needs and reduce the imbalance of the grid.
- **Capacity Market Program (CMP)** is a market-based program offered solely to consumers who can provide flexibility. Enrolled users will be rewarded regardless of whether they are called and penalised if they fail to deliver after committing themselves.

DR-RISE will focus on three DR approaches: those mentioned above and the so-called **Manual Load Shifting (MLS)**, a simplification of DLC in which users can manually adjust their consumption load by scheduling their appliances. While MLS is suitable for users wanting greater control over their system or who cannot afford the installation to automate DR, DLC is thought for users willing to cede control authority over their appliances in exchange for a lower complexity. Finally, CMP is offered to those voluntary candidates who are the most advanced users, however, in contrast to its definition, DR-RISE will guarantee them that no penalties will apply.

1.2.2 Current status and future development

Most of the DR approaches in the literature follow the same pattern: they optimise the end-consumers' assets through an objective function willing to minimise the energy costs while considering the DR schedule simultaneously [2]. To achieve this purpose, it is essential to account for several uncertain parameters, such as meteorological conditions, energy prices, or energy consumption. Although the real-time availability of this data is possible, forecasting is required to provide the grid with predictions of the available flexibility, which can be achieved using algorithms based on Artificial Intelligence (AI).

However, due to the complexity of DR and the variety of agents and disciplines involved, the literature review shows that all approaches have certain disadvantages [3] [4], such as:

1. Reducing the number of actors involved, focusing solely on end consumers or aggregators.
2. Assuming that all end-users are identical, e.g., treating all users as prosumers involved with electric mobility or PV generation, while some may be pure consumers or prosumers with different profiles.
3. Ignoring empirical results may compromise their reliability in real applications, for example, due to a lack of commitment from end users.

Within this framework, DR-RISE proposes a Model Predictive Control solution combined with AI-based predictions to manage uncertainties and optimise the energy flow within a household, enhancing the security and reliability of the power system. To overcome the challenges raised in the literature, a two-layer optimisation will be deployed to account for consumers, aggregators, and energy system operators. In addition, a local objective function will be designed to consider each end-user individually, considering household disparities.

Besides employing a simulation environment during the early stages of the project, DR-RISE will test the solution in three empirical demonstrators located in different climatic environments and socio-economic contexts. The demonstrators will serve both for validation and to identify additional challenges.

1.3 Optimisation architecture

The DR-RISE optimisation architecture is based on **Smart Nodes** that include the necessary tools to optimise and manage energy flows, and it is implemented through a two-layer approach.

The **User Smart Node (USN)** manages local energy assets at a household level to balance cost savings with user comfort. In addition, energy usage and availability are predicted throughout a forecast module based on historical and real-time data. Moreover, the USN layer will provide end-users with tools to overcome hindrances and enable their participation in DR mechanisms.

Meanwhile, the **Aggregator Smart Node (ASN)** interacts with grid operators. It is responsible for the real-time distribution of DR requirements to individual USNs, ensuring optimised load management for the grid. In addition, it relies on a set of AI-based forecasts derived from USN data for aggregate demand and estimation of response capacities for DR compliance.

Both modules are bi-directionally connected since USN is required to send information regarding its consumption and flexibility possibilities, while at the ASN level, the DR events are notified. However, it should be noted that there is no communication between the different USN modules. While this communication might be beneficial from a cooperative point of view, the DR-RISE project has decided to isolate them to prevent drawbacks regarding information sharing with unknown users and thus promote user engagement.

1.4 Challenges

Technical barriers

- **System complexity.** The integration of different energy assets, such as RES and ESS, increases the complexity of the HEMS' optimisation. Thus, the underlying control algorithms must deal with multi-objective optimisations, such as reducing energy use, maintaining comfort, and achieving demand response compliance.
- **Computational constraints.** As the number of assets increases, the optimisation requires substantial computational resources, especially when working with MPC approaches, which optimise its objective function for an entire prediction horizon. However, advancements in computational power (including IoT devices) and solvers for Mixed Integer Linear Programming (MILP) and Mixed Integer Quadratic Programming (MIQP) have mitigated this challenge. Therefore, MPC strategies are suitable for multi-objective HEMS optimisation.
- **Real-time decision-making.** Some DR programs require near real-time responses to grid signals, which challenges the latency and processing capabilities of HEMS, particularly in more extensive, distributed networks.

- **DR signal protocol compatibility.** While unified standards for managing DR signals have not yet been established in the EU, communication currently relies on specific interfaces developed by individual TSOs, DSOs, and market operators. The DR-RISE optimisation module must ensure compliance with these interfaces and adapt to them for smooth communication and operation within the regulatory and technical framework, which may vary across regions.

Regulatory barriers

- **Compliance with National standards.** Mainly at the ASN level, the optimisation must comply with National regulations regarding energy aggregation and participation in DR programs.
- **Data management regulations.** The optimisation algorithms must respect national and international regulations that restrict how data can be collected, stored, and shared. Ensuring compliance without compromising optimisation performance poses significant challenges, especially with near real-time data requirements.

Social barriers

- **User engagement.** This aspect is paramount for successfully implementing DR solutions. Encouraging residential users to participate actively in DR programs and energy optimisation initiatives can be challenging. Many consumers may have limited familiarity with energy management systems and may perceive them as complex or intrusive, particularly when required to adjust energy use based on external signals. As introduced in Section 1.2.1, users can adopt an automated or manual DR approach, depending on whether they wish to increase their control, and the level of effort involved.
- **Up-front cost.** Berring capital investment of the EMS system that would provide money savings and/or reward is a barrier for the end-user and especially for those who would most need cost optimisation.
- **Privacy concerns.** This essential aspect can directly affect user engagement, as users may hesitate to share data for optimisation. Users may be concerned about sharing information such as energy usage data, which could reveal personal habits and household activity patterns.
- **Impact on comfort.** Optimisation strategies, such as load shifting to reduce peak demand, may conflict with consumers' lifestyles and preferences. For example, limiting or scheduling the use of appliances may be perceived as a disruption, which could reduce engagement with the optimisation solution. Additionally, the expected loss of comfort often differs from the actual impact, especially in homes with technologies such as heat pumps or batteries, where advanced management can minimise disruptions while maintaining comfort.

1.5 Socio-economic benefits

Among the different benefits of applying DR approaches through the proposed optimisation, we can identify:

- **Reduced costs for consumers.** DR reduces consumers' electricity bills and overall energy costs by enabling end-users to adjust their energy consumption in response to price signals or incentives.
- **Increased grid stability and efficiency.** DR approaches provide ancillary measures to the grid, introducing energy flexibility by effectively balancing supply and demand.
- **Enhanced energy democracy.** DR solutions can reach a wide range of user profiles, allowing low-income households to benefit from reduced energy costs and greater control and knowledge of their consumption.
- **Social benefits for energy poverty.** The adoption of DR programs has the potential to overcome energy poverty by, for example, developing business models in which DR savings are pooled and redirected to assist vulnerable and low-income users.
- **Integration of RES.** DR provides a flexible demand that can cope with intermittent supply, thereby promoting and facilitating the integration of renewable energy resources and their underlying investments.
- **Environmental benefits.** Besides the opportunity for a greater deployment of RES, DR enables de reduction of peak demand, which entails a lower dependency on fossil fuel power generation. Hence, DR programs also reduce greenhouse gas emissions, steering society towards the energy transition.

2 Optimisation overview

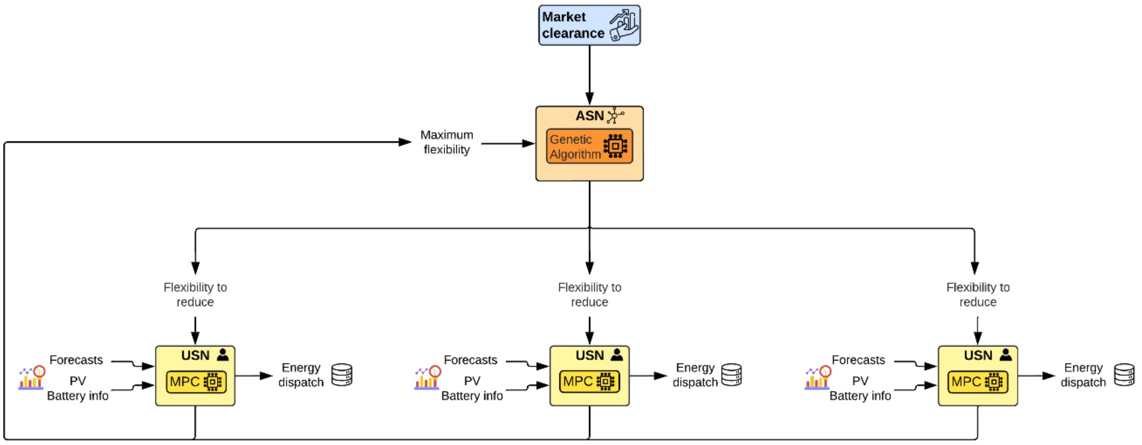

Figure 2. Overview of the DR-RISE optimisation

As illustrated in Figure 2, the optimisation architecture is structured into two distinct modules: the **User Smart Node (USN)** and the **Aggregator Smart Node (ASN)**. Each module is responsible for a specific type of optimisation, tailored to achieve different outcomes. Despite being independent modules, they are interconnected, with the output of one feeding into the input of the other.

On the one hand, the USN optimisation is performed hourly, receiving inputs such as solar production (if the user has a PV panels), energy consumption and electricity price forecasts, as well as specifications regarding Energy Storage System (ESS), if applicable. In case the electricity tariff is dynamic, i.e., changing every hour for instance, this constitutes the price-based demand response (PBDR). Additionally, in some cases, the USN will receive another input: the flexibility to reduce, which is the output of the ASN optimisation and constitutes the incentive-based demand response (IBDR) approach. This flexibility value specifies how much energy the user should reduce at a specific time. Using this information, the USN performs a mathematical optimisation based on the **Model Predictive Control (MPC)** framework (further detailed in Section 3.2), producing the optimal energy dispatch for the next 24 hours. This output indicates the amount of energy to be bought from the grid, utilised from the PV panel or battery (if available) and sold back to the grid.

Furthermore, the ASN, when necessary, will receive as inputs the maximum flexibility that each of the users can offer at a given date and time, as well as the total flexibility required by the market. With this data, the ASN conducts a heuristic optimisation using a **Genetic Algorithm (GA)** (see Section 4.2), determining, as a result, the amount of energy that each user should reduce at the designated time. This result translates into specific user actions, such as modifying behaviour by avoiding the use of certain appliances during demand and supply imbalances.

The following sections will delve into each module in more detail, establishing the theoretical foundations that underpin the respective optimisation processes and providing a comprehensive outline of their workflows.

3 USN optimisation

3.1 Overall approach

As introduced in the previous section, the USN is responsible for determining the energy dispatch that maximises monetary savings for the user. Every hour, the USN gathers predicted values for solar production, household energy consumption, electricity price, and feed-in tariff for the upcoming 24 hours, as well as information related to a photovoltaic panel or battery, if applicable. Subsequently, it builds an MPC model including variables, parameters, constraints and an objective function. The USN then performs the optimisation, giving, as a result, the next control action, i.e., the energy flow between the grid, the PV panel, the battery and the household in order for the cost to be minimised.

3.2 MPC

3.2.1 General description of the framework

Model Predictive Control is an advanced process control technique introduced in the late 1970s and has since become widely used [5]. This method entails solving an open-loop optimal control problem at each timestamp within a predetermined prediction horizon *N*. With each iteration, MPC executes the first input from the established optimal control sequence and then recalculates for the subsequent decision point.

MPC utilises a comprehensive mathematical model of the system it controls. This model is paramount since it describes how the system's outputs respond to the different control inputs. At each instant *k*, MPC first collects the latest data to update the system's current state. Then, it uses this information together with the mathematical model to minimise an objective function and obtain an optimal control strategy over the prediction horizon *N*. Additionally, only the first control action from this optimal sequence is implemented at each step.

A key feature of MPC is its receding horizon strategy. This means that after the first control action is applied, the horizon moves forward to the instant *k+1*, gathering new data to update the system's state. The process then repeats, using this new information and the mathematical model to recalculate a new optimal control strategy, ensuring that the control sequence remains optimal in response to changes and disturbances.

Consequently, the MPC strategy consists of the following steps [6]:

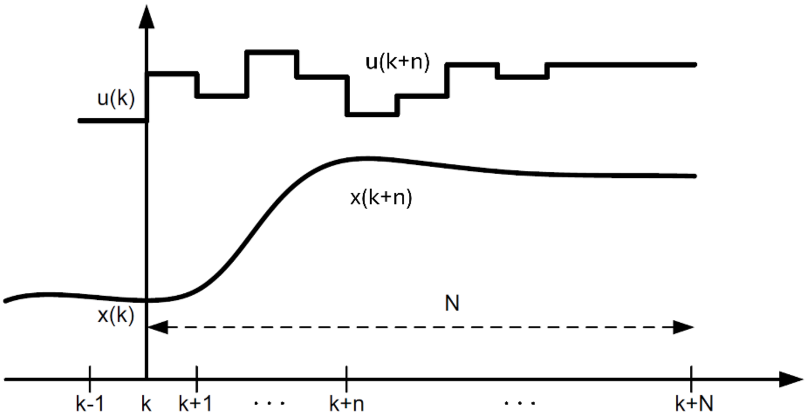

Figure 3. MPC Strategy [6]

1. The future state over the prediction horizon *N* is predicted at each instant *k* using the mathematical model. This future state $[\,x(k+1),\dots,x(k+N)]$ depends on both the historical state up to the current instant *k* and the future control actions $[u(k),u(k+1),\dots,u(k+N-1)]$.

2. The future control signals are determined by performing an optimisation aimed at minimising an objective function defined in terms of the control actions over the prediction horizon. This minimisation is subject to the system's dynamics over the horizon, the system's constraints, and the initial state of the system at the beginning of the current control period.

3. The calculated control signal $u(k)$ is dispatched to the process, and the next control signals are rejected. This occurs because by the next sampling time, the state $x(k+1)$ is already known and step 1 is repeated, updating this value and all the sequences accordingly. This results in the re-computation of the predicted control signal $u(k+1)$, which does not necessarily have to be equal to the one computed at instant *k*.

This strategy is implemented using the basic structure shown in Figure 4. This involves utilising a model to predict the future outputs based on past and present data as well as on the proposed optimal future control actions. These actions are determined by the optimiser, considering the objective function and the system's dynamics, constraints, and measurements of the initial state [5].

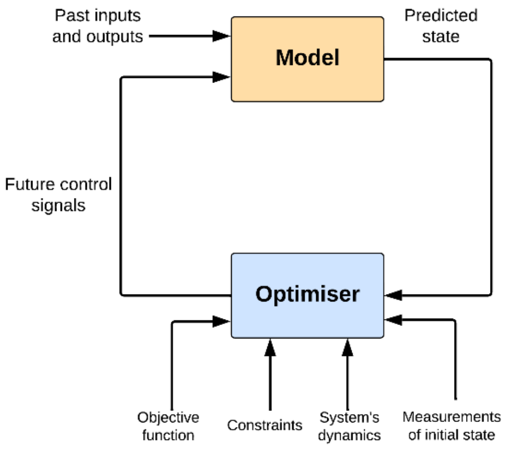

Figure 4. Basic structure of MPC

3.2.2 MPC applied to our use case

The first step involves generating a mathematical model of our system. To this end, the Energy Hub Modelling framework detailed in [6] has been applied.

Following this approach and after analysing the types of modules and components that can be present in a generic modern household, the Energy Hub diagram considered is depicted in Figure 5.

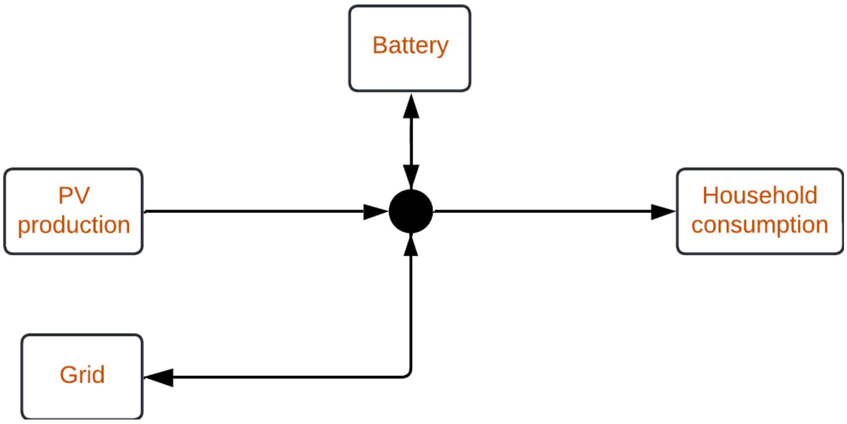

Figure 5. Model hub diagram

3.2.2.1 Variables and parameters

Once the diagram is established, the next step encompasses translating it into mathematical equations, for which some variables and parameters must be declared first.

- The **decision variables** to be considered are, basically, the amounts of energy that can flow through each of the links (i.e., how much energy should be bought from the grid, sold to it, taken from the PV panel or stored/consumed in/from the battery if the user has PV or battery, respectively), as well as the state of charge (SOC) of the battery, if applicable. Additionally, some other auxiliary variables are considered in order to remove the quadratic terms present in some equations and, hence, transform quadratic equations into MLD (Mixed Logical Dynamical).

- The **parameters** involved are those which are needed inputs of the model, namely:
    - Forecasts related to PV production, consumption, electricity price and feed-in tariff.
    - Upper and lower bounds of the variables.
    - Initial values of the variables.
    - Specifications about the battery (positive and negative efficiency, maximum charge and discharge power, etc.).
    - Other parameters used to transform quadratic equations into MLD.

3.2.2.2 General constraints of the system

Having all the information about available decision variables and parameters, the model can be defined. In order to do so, several constraints are defined. These constraints will be used to represent the mathematical equations that govern the dynamics of the system, ensuring that the model aligns with the underlying principles and behaves as expected. Some of these are related to the aggregation or disaggregation of power across different points in the system, effectively modelling the flow and distribution of energy, and ensuring that the energy demand is met.

Furthermore, the model incorporates additional constraints that will impose operational boundaries and safety limits that the system must adhere to under all circumstances and that are essential for maintaining the feasibility of the model's operation. These constraints include restrictions on the decision variables not exceeding the thresholds established by the upper and lower bounds as well as complying with the initial values.

One equation that is worth commenting on is the one that models the behaviour of the battery [6]. Initially, it is described as:

$$soc(h+1) = soc(h) + \lambda(h) \cdot s(h) \cdot T_s \qquad (1)$$

$$\text{with} \qquad \lambda(h) = \begin{cases} e^+ & if \;\; s(h) \geq 0 \\ 1/e^- & if \; s(h) < 0 \end{cases}$$

where:

- $soc(h)$ represents the state of charge of the battery in the instant h .
- e^+, e^- are the charging and discharging efficiencies of the battery, respectively.
- T_s is the sample time (i.e. the duration of a timestamp).
- $s(h)$ is the amount of energy flowing into or out of the battery, depending on whether the value is positive or negative, respectively.

This equation models the SOC of a battery at the next instant as being equal to the current SOC plus the net energy added or removed. This change accounts for the energy flow, either into or out of the battery, and adjusts for the respective charging or discharging efficiencies.

As can be seen, this equation incorporates a quadratic term, $\lambda(h) \cdot s(h)$, which is difficult to address from a computational point of view. In order to solve it, some auxiliary variables, parameters, and constraints have been introduced to transform the quadratic equation into an MLD problem [7]:

- **New variables:**
    - $\delta(h)$: a binary variable.
    - $r(h)$: a non-negative continuous variable.

- **New parameters:**
    - ε: a very small value.
    - m: a value equal to the lower bound of $s(h)$.
    - M: a value equal to the upper bound of $s(h)$.

- **New constraints:**
    - $-m \cdot \delta(h) \leq s(h) - m$ *(2)*
    - $-(M + \varepsilon) \cdot \delta(h) \leq -s(h) - \varepsilon$ *(3)*
    - $r(h) \leq M \cdot \delta(h)$ *(4)*
    - $r(h) \geq m \cdot \delta(h)$ *(5)*
    - $r(h) \leq s(h) - m\big(1 - \delta(h)\big)$ *(6)*
    - $r(h) \geq s(h) - M(1 - \delta(h))$ *(7)*

Inequalities *(2)* and *(3)* are equivalent to the logical rule

$$\delta(h) = 1 \leftrightarrow s(h) \geq 0$$

while inequalities *(4)* - *(7)* are equivalent to

$$r(h) = s(h) \cdot \delta(h)$$

Therefore, $\delta(h)$ will take the value **1** if the battery is charging or idle, and **0** if it is discharging, hence, $r(h)$ will take the value of $s(h)$ if the battery is charging or idle, and **0** if it is discharging.

Consequently, equation *(1)* can be transformed into:

$$soc(h+1) = soc(h) + \left[\frac{1}{e^-} \cdot s(h) + \left(e^+ - \frac{1}{e^-}\right) \cdot r(h)\right] \cdot T_s$$

where there are no quadratic terms.

3.2.2.3 Objective function

The final step in developing the model is to define the objective function, which will outline the goal of the model. For this scenario, the objective is to optimise the energy dispatch of the next 24 hours to minimise monetary costs. As a result, the cost function must incorporate a term of the form:

$$\sum_{h=0}^{N-1} \left(e_p(h) \cdot p(h) - e_s(h) \cdot f_t(h)\right)$$

where N is the 24-hours horizon, e_p is the energy purchased from the grid, p is the electricity price, e_s is the energy sold to the grid, and f_t is the feed-in tariff. This term represents the direct benefit associated with energy consumption and sale since, in our model, the energy sources include the grid and, optionally, energy generated from a photovoltaic panel, which incurs no monetary cost, and the second term in the summation represents the sale of energy to the grid.

Moreover, since we are continuously working with forecast data, it is essential to adapt the objective function to reflect the dynamic nature of this information. To this end, the cost function also includes a term that assigns greater weight to more recent forecast data for PV production. This way, the model uses more PV energy in the earlier timestamps than in the later ones, prioritising the closest forecasts to the current moment in time, enhancing the accuracy and reliability of the strategy. Accordingly, the objective function will also incorporate the following term:

$$\sum_{h=0}^{N-1} \left(-\frac{\varepsilon}{(h+1)} \cdot PV(h)\right)$$

where $PV(h)$ is the energy coming from the photovoltaic panel at the instant h.

Additionally, the objective function includes a penalisation term specifically designed to maintain the SOC of the battery above a fixed threshold. Initially, this could be thought of as a constraint. However, there are scenarios where the SOC could begin below this threshold, potentially leading to violating the constraint and rendering the model unsolvable. To avoid this, the strategy followed involves heavily penalising whenever the SOC falls below the threshold. As a result, if the SOC starts at a low level, the model prioritises recharging the battery to ensure that the SOC remains above the minimum required. Therefore, the last term of the objective function would be:

$$\mu \cdot \sum_{h=0}^{N-1} (1 - \theta(h))$$

where μ represents the penalisation and θ is a binary variable indicating whether the SOC threshold has been surpassed (**1**) or not (**0**).

Recapitulating, the final objective function to be minimised would be the following:

$$\sum_{h=0}^{N-1} \left[e_p(h) \cdot p(h) - e_s(h) \cdot f_t(h) - \frac{\varepsilon}{(h+1)} \cdot PV(h) + \mu \cdot (1 - \theta(h)) \right]$$

As it can be seen, the objective function seeks reducing the costs of the end-user as much as possible, which is the same, as maximising their savings. Although this may seem purely economic as it is, reaching this objective is also directly related with environmental and social objectives.

The environmental objective is reached thanks to three facts. The first of them is that the MPC naturally prioritises the use of PV energy over that from the grid, thus using completely renewable energy whenever possible. The second is related to how Battery Energy Storage System (BESS) is managed in case the user owns one. The BESS will charge from the previous PV energy or when the electricity prices are lower and will discharge when the electricity prices are higher. In the energy market, the electricity prices are low when there is a large contribution of renewable energies to the grid and high when this is not possible (e.g., outside of sunlight hours). This is represented in Figure 6, where this relationship is perfectly visible.

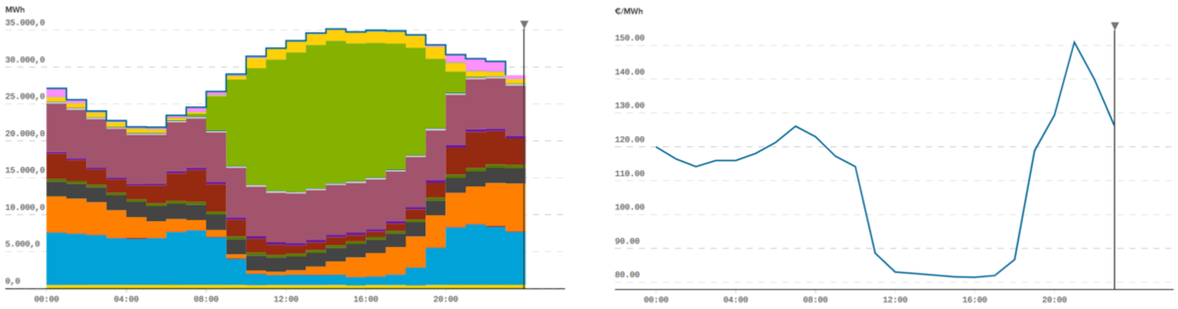

Figure 6. Energy in the pool by source type (left) and SPOT market price in Spain (right). Solar PV generation is represented in light green

The last fact is the inclusion of DR, which is an approach specifically design to address the imbalance between supply and demand when supply is not enough to meet the current demand. Historically, this balance was achieved by producing electricity in non-renewable power plants thanks to their fast ramp-up capabilities. Nevertheless, this energy typically comes from fossil fuels and is significantly more expensive. DR offers an alternative to avoid relying on these power plants when there are imbalances, and these approaches are incorporated into the MPC. Therefore, the optimisation problem formulated naturally strives for environmental objectives as well.

Finally, regarding social objectives, these approaches can be used to alleviate the energy poverty factor. IBDR, as the name suggests, entails a monetary incentive for those users who comply with the energy reduction requested. A business model could be implemented that donates part of these savings for those energy poor people within the energy community where implemented. While the optimisation problem cannot directly encapsulate this per se, it can for sure be a catalyst to allow new measures to alleviate this problem.

3.2.2.4 Demand Response constraints

As introduced in Section 2, there will be times when the USN will receive one additional input: the flexibility – the amount of energy that the user should reduce – and the specific time at which it should be curtailed. This input comes as an output of the ASN optimisation (which will be explained in detail in Section 4), in compliance with explicit (i.e. incentive-based) Demand Response (DR).

Incentive-based DR (IBDR) involves offering economic incentives to consumers to encourage them to adapt their electricity usage during hours of demand and supply imbalances. In DR-RISE, IBDR is addressed by distributing an ASN's required flexibility across all its users after receiving a DR signal from the market. This distribution considers each user's individual reduction capacity.

Therefore, when the USN receives the flexibility requirements for the optimisation (which includes both the required reduction and the target time), it incorporates additional variables, parameters, and constraints into the model. The approach unfolds as follows:

1. A new decision variable is introduced to identify the most suitable alternative time to consume the specified amount of energy.
2. New constraints are created to ensure that this block of energy is not used during the reduction time.

Figure 7 provides a visual example of this functionality applied to a shiftable appliance. In this scenario, the market sends a DR signal so as to decrease consumption at timestamp 9. The ASN conducts its optimisation and decides how much energy should be reduced by each user. After receiving the details, the USN carries out its own optimisation, shifting the reduction block to a more optimal timestamp.

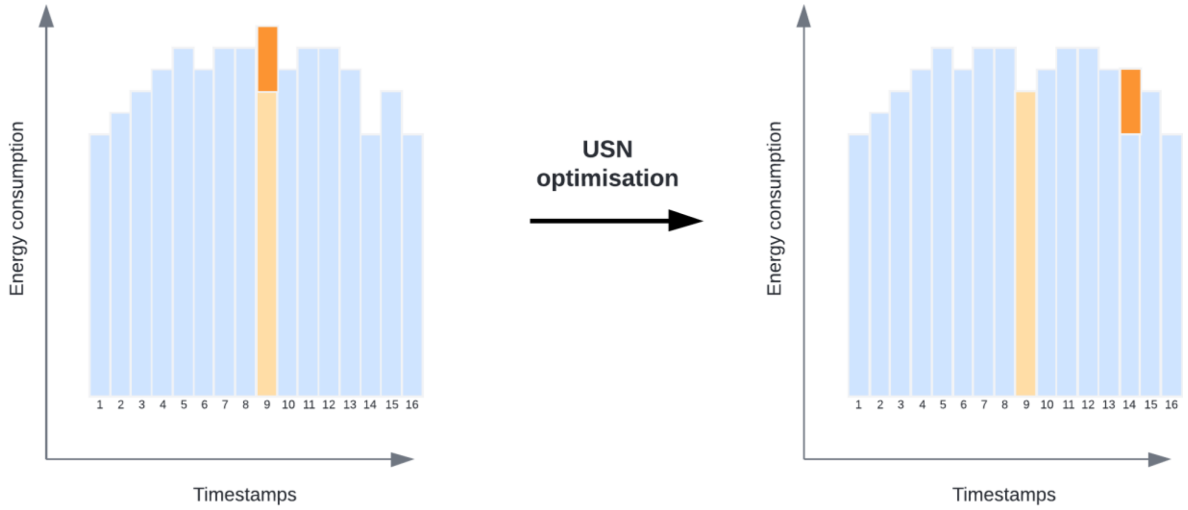

Figure 7. Incentive-based Demand Response (IBDR) in USN

3.3 Demand Response Clock Workflow

Another functionality that the USN implements is the “Demand Response Clock”, which operates as a traffic light-style indicator system designed to engage users in improving their consumption strategy.

The process begins by incorporating an additional load into the model. Multiple optimisations are then conducted, with the additional load being positioned at different timestamps across the model. For each configuration, the value of the objective function is analysed, providing a comprehensive evaluation of how different consumption timings affect costs.

Once the cost analysis for each hour is completed, a clustering algorithm is applied to the data. It categorises each hour into one of three categories: high (red), medium (orange), and low (green). The categorisation will be visually represented through the Demand Response Clock, enabling users to easily understand and adapt their energy usage to the optimal times, as exemplified in Figure 8.

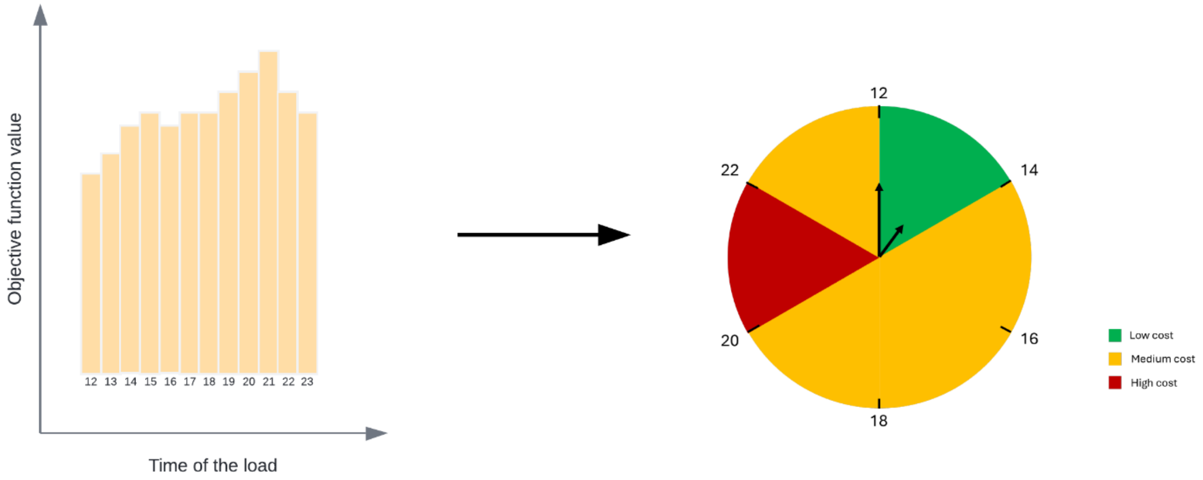

Figure 8. Demand Response Clock

3.4 Maximum flexibility from users

The last workflow of the USN centres on calculating the maximum flexibility that each user can offer. As outlined in Section 3.2.2.4, on some occasions, the ASN will determine how much energy a user should reduce at a specific time. However, before making this decision, the ASN requires information on the maximum amount of energy that could be potentially reduced by each user. With this data, the ASN can analyse whether it is necessary for a user to make the reduction.

In order to obtain a user's maximum flexibility at a target time, the first step is to compute the probability of each appliance being activated. This probability is derived from the ratio of the number of days an appliance has been used at that specific time since the first record to the total number of days recorded, with a differentiation between weekends and weekdays.

Once these probabilities are calculated, any appliance with a probability exceeding a predetermined threshold is added to a set of potential contributions. After assessing all the appliances, the user's maximum flexibility at that target time is determined as the power rate of the appliance with the highest usage probability from this set. In case none of the appliances meet the threshold – the set is empty – the user will provide no flexibility at that time.

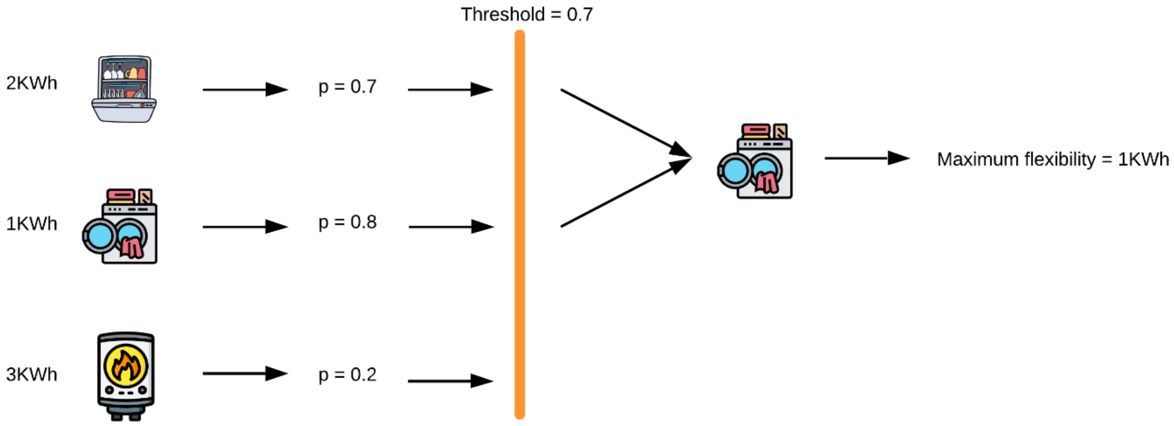

Figure 9. Determination of a user's maximum flexibility

It is worth noting that this strategy has been implemented due to regulatory constraints that prevent the involvement of a real aggregator in the pilots. Consequently, its functions have been simulated following consultations with an actual one. The integration of an aggregator would enable the employment of more advanced techniques for managing this flexibility. As an example, VOLTALIS uses a statistical model based on machine learning techniques to provide the estimated consumption based on external conditions such as temperature or calendar data. This estimated consumption represents the flexibility offered to the market.

4 ASN optimisation

4.1 Overall approach

The Aggregator Smart Node (ASN) is responsible for carrying out the Incentive Based Demand Response. As previously introduced, during electricity supply and demand imbalances, the market may request some flexibility from the ASN. To fulfil this, the ASN distributes the required reduction among its associated users. This distribution is performed applying a Genetic Algorithm, which aims to minimise the gap between the requested and achieved flexibility. The algorithm also accounts for each user's potential contribution, while prioritising users with higher participation rates and those who have been asked to contribute less frequently, in order to give all users the opportunity to participate.

The workflow begins with the ASN making an offer to the market for each hour of the next day. In order to compute the offer for a specific hour, the following steps are taken, as illustrated in Figure 10:

1. The *aggregated flexibility* is computed as the aggregation of the maximum flexibility of each user at that hour, by following the approach described in Section 3.4.

2. The *adjusted aggregated flexibility* is determined as the flexibility provided by the users with participation rate above a threshold. This participation rate is calculated as the quotient between the number of times that the user has accepted to participate in a DR event and then complied, and the number of times that it has been asked to participate.

3. The *adjusted aggregated flexibility after backup* is calculated as a percentage of the previous flexibility of that hour, saving some for backup, and is then offered to the market.

4. The market may accept all or part of this flexibility, resulting in the *cleared flexibility*, which is then distributed among users using the Genetic Algorithm.

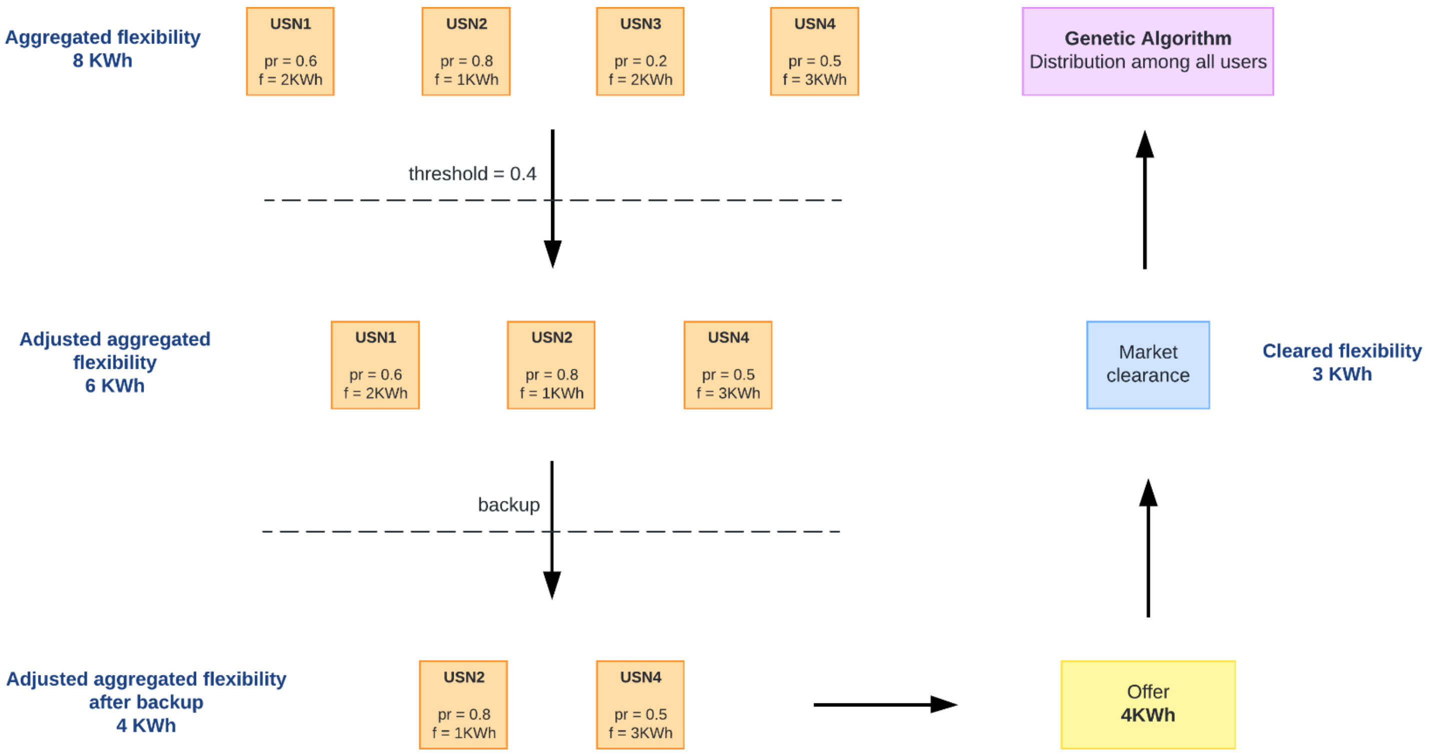

Figure 10. Calculation of the market offer

4.2 Genetic Algorithm

4.2.1 General description of the algorithm

Genetic Algorithms (GAs) are heuristic search methods that mimic the process of natural selection [8, 9]. They are designed to solve complex problems where optimal solutions are not easily found using conventional methods and aim to find approximate or exact solutions to optimisation and search problems. The general approach involves transforming a population of potential solutions over several iterations until one of them is good enough (i.e., an end criterion is met).

The main components of GAs include:

- **Chromosome**: individual representing a potential solution.
- **Gene**: fundamental unit of a chromosome, representing a specific attribute of the solution.
- **Population**: a collection of chromosomes that comprises the current set of potential solutions.

- **Fitness function**: a function used to evaluate the quality of each chromosome, assigning a score that reflects how well it solves the problem.

- **Search space:** the set of all possible solutions to the problem.

The methodology of a Genetic Algorithms generally follows these steps (Figure 11):

1. **Initialisation**: the algorithm starts with a randomly generated population of chromosomes within the search space.

2. **Evaluation**: each chromosome in the current population is evaluated using the fitness function. If the termination condition is met (such as reaching a maximum number of generations or finding a solution with a satisfactory fitness score), the algorithm stops, and the best chromosome of the current population is considered the solution. Otherwise, the algorithm continues.

3. **Selection**: some chromosomes are selected from the current population, based on their fitness score, to form a new generation.

4. **Crossover**: pairs of selected chromosomes are chosen to recombine their genes in order to generate new chromosomes (offspring).

5. **Mutation**: the offspring is transformed by randomly mutating some of its genes.

6. **Replacement**: one or more chromosomes from the last generation may replace one or more in the newly generated offspring, creating the new generation and returning to step 2.

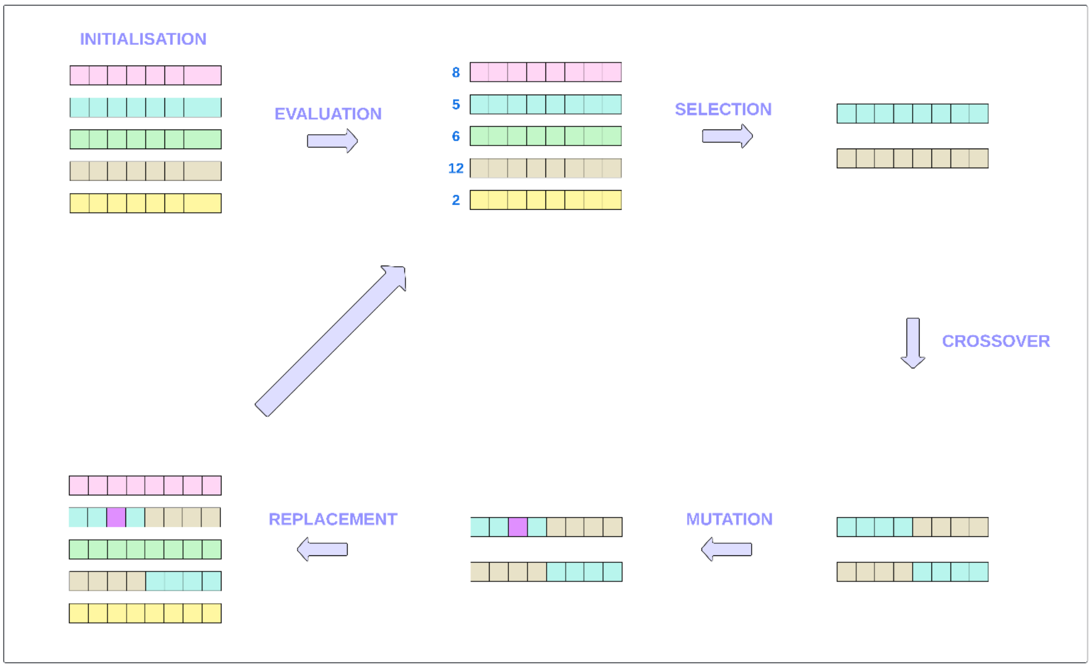

Figure 11. Genetic Algorithm overall strategy

4.2.2 Genetic Algorithm applied to our use case

Our main goal is to distribute a specific quantity (the required flexibility) across a group of users, taking into consideration each user's capacity to reduce. This is an instance of the Subset Sum Problem (SSP), a particularisation of the famous Knapsack Problem (KP), and Genetic Algorithms have demonstrated to be effective when solving this kind of problems [10].

The Knapsack Problem involves a set of items, each of them with a designated value and weight. The objective is to find the optimal combination of items that achieves the highest value without the total weight exceeding a pre-defined capacity. The Subset Sum Problem is a particular case of the KP, focusing on selecting a subset of numbers from a given set to exactly match a target sum. Mathematically, the Knapsack Problem is formulated as:

$$Maximise: \quad \sum_{i=0}^{N-1} v_i \cdot x_i$$

$$Subject\ to: \quad \sum_{i=0}^{N-1} w_i \cdot x_i \leq c$$

where x_i can take de value **1** or **0**, depending on whether the item i is included or not, v_i and w_i are the value and weight of the item i, respectively, and c is the maximum capacity.

4.2.2.1 Initial representation and fitness function

Our chromosomes will be represented as Integer vectors, with the length corresponding to the number of users. Each component, or gene, indicates whether a user is included in the reduction effort – represented by its **reduction capacity** (the user is participating), or a **0** (the user is not participating). The space length is then the set of possible combinations of user participation.

On the other hand, since the objective is to reach a target number by summing the contribution of the participants, the optimisation problem can be considered as a minimisation of the difference between the required flexibility and the quantity achieved through the sum of each participant's contribution. Consequently, the fitness function incorporates a term of the form:

$$-w_1 \cdot \left| r_f - \sum_{i=0}^{N-1} f_i \right|$$

where r_f represents the required flexibility, N is the number of potential participants, f_i denotes the current value of the gene i (i.e., the flexibility that user i is asked to reduce), and w_1 is the weight associated to this term.

Additionally, in order to ensure compliance and effective participation, it is important to prioritise users with high participation rates. Thus, another term of the fitness function is:

$$w_2 \cdot \sum_{i=0}^{N-1} p_i f_i$$

where p_i is the participation rate of user i, and w_2 is the weight given to this term.

Lastly, if only users with high participation rates are prioritised, less frequent participants could be excluded. To avoid this, users who have been asked to participate the least are also considered, leading to the incorporation of the following term:

$$-w_3 \cdot \sum_{i=0}^{N-1} a_i f_i$$

where a_i represents the number of times that user i has been asked to reduce consumption.

Therefore, the fitness function to be maximised is:

$$-w_1 \cdot \left| r_f - \sum_{i=0}^{N-1} f_i \right| + w_2 \cdot \sum_{i=0}^{N-1} p_i f_i - w_3 \cdot \sum_{i=0}^{N-1} a_i f_i$$

4.2.2.2 GA Strategy

The steps explained in Section 4.2.1 are tailored to meet the requirements (Figure 12):

- **Initialisation:** the initial population is created randomly, with each gene in each chromosome taking, arbitrarily, one of two possible values: 0 or its reduction capacity.

In each iteration, a new potential population is generated, by applying the following steps:

- **Evaluation:** each chromosome of the current population is evaluated by applying the fitness function described in the previous section.

- **Selection:** using the *Binary Tournament*, which, for each chromosome to be created for the new generation, two individuals are chosen randomly from the last generation (with replacement), and the best of them (in terms of their fitness score) is selected to be part of the new generation.

- **Crossover:** after selecting the chromosomes, these are systematically paired, and each pair undergoes a *Uniform Crossover* at a predetermined probability. In the *Uniform Crossover*, two offspring are created from two parent chromosomes. To do so, a random decision determines the gene distribution between the offspring: if one child inherits a gene from one parent, the other child automatically inherits the gene from the other parent, ensuring that both offspring receive a balanced mix of genetic material from both parents.

- **Mutation:** each gene within every chromosome of the generated children has a probability of mutating. This mutation involves swapping the current gene value. Specifically, if the current value is 0 (indicating non-participation), it is changed to the user's reduction capacity (indicating participation), and vice versa.

- **Replacement:** following an elitist approach, once a new potential generation is created, each chromosome is re-evaluated. If the worst chromosome in the new generation is inferior to the best chromosome from the previous generation, the former is replaced by the latter, ensuring that the quality of the population does not degrade over generations.

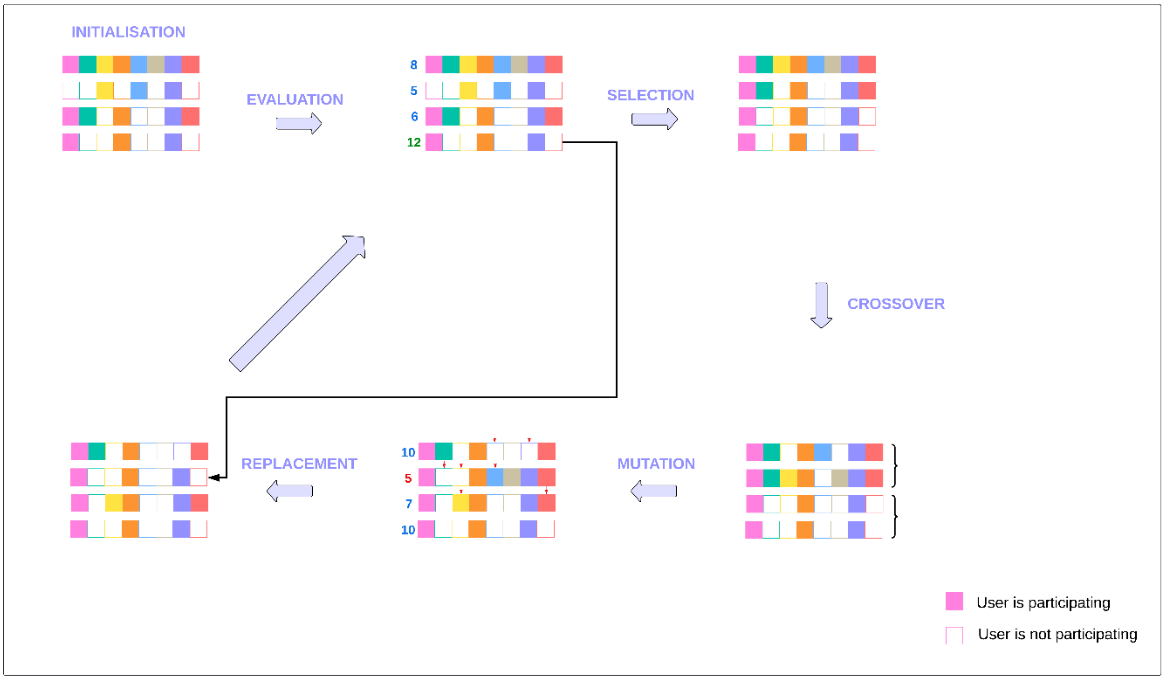

Figure 12. Genetic Algorithm applied to our use case

4.3 Flexibility distribution and user notification

It has already been explained how the required flexibility is determined and distributed among the different users. This is part of a larger pipeline that involves several steps of calculations and notifications.

Every time IBDR is required, flexibility offers for each hour of the upcoming day are submitted to the market, as outlined in Section 4.1. The Genetic Algorithm preliminarily distributes the *cleared flexibility* for each hour among the users, ensuring that each user is only asked once per day. Consequently, a user will appear in only one of these preliminary allocations.

After the preliminary distribution of required flexibility, the following four steps are executed for each DR event:

1. Four hours before the event, notifications are sent to the users designated by the preliminary distribution, asking them whether they could achieve the specified reduction.

2. Two hours before the event, responses to the initial notification are collected. If a user accepts to participate, no further action is taken. Otherwise, its flexibility is accumulated, so the total flexibility relative to all the users who rejected their participation is re-distributed with a second instance of the Genetic Algorithm among those users not initially asked. A second notification is then sent to these users to confirm their participation.

3. At the time of the event, responses to the second notification are collected. If a user now agrees to participate, no further action is required. If not, its flexibility is also accumulated.

4. At the time of the event, the flexibility from users who declined to participate in the second notification, and from those who agreed but did not comply with the reduction, is taken from a backup, which consists of various assets in the aggregator’s portfolio, such as batteries (either from users or standalone units), which are able to supply this capacity immediately.

4.4 Baseline consumption calculation

The previous sections have frequently discussed the need for flexibility reduction. However, to quantify these reductions, it is essential first to establish a consumption baseline. This baseline will act as a reference point against which all reductions are measured.

To do so, we have examined how various Transmission System Operators (TSOs) from different countries calculate this consumption baseline [11, 12, 13], and have opted for the approach followed by the Greek TSO [13], due to its simplicity and suitability for our specific requirements. However, it is important to note that these methodologies are primarily tailored for major consumers, including industrial and commercial sectors. Consequently, subsequent iterations will include the evaluation of additional methodologies to assess their applicability for residential users.

The Greek methodology involves the following steps:

1. **Determination of the Look-Back Window**: it is defined as the 45 most recent days prior to the day of the DR event. It will serve as the historical period from which eligible days are selected for the baseline calculation.

2. **Dispatchable Load Portfolio Window Determination**: this window consists of days from the Look-Back Window that are representative of typical consumption patterns without DR interventions:

    a. For weekdays, it is defined as the 10 most recent weekdays (excluding weekends, public holidays, and days with DR events) within the Look-Back Window. If 10 eligible days cannot be identified, at least 5 days may be used. If fewer than 5 eligible days are available, days with DR events can be included, prioritising those with the highest average consumption.

    b. For Saturdays, it is defined as the 3 most recent Saturdays without DR events. If only 2 eligible Saturdays are available, they may be used instead.

    c. For Sundays and public holidays, it is defined as the 3 most recent Sundays or public holidays without DR events. If only 2 eligible days are available, they may be used instead.

3. **Initial Baseline Calculation**: this step establishes the expected load profile for the DR event period in the absence of DR intervention (i.e. what the load would have been during the DR event if no DR was occurring). To that end, the "*High X of Y*" method is applied, where the X highest-consuming days from the Y days defining the Dispatchable Load Portfolio Window (during the time period of the DR event). After selecting these X highest consumption days, the average load for each hour during the DR event period is computed by taking the hourly consumption values from each selected day and calculating their mean.

4. **Baseline Adjustment**: an additional adjustment is applied to align the baseline with the conditions of the day of the DR event. This adjustment accounts for daily variations by comparing the average consumption in the Adjustment Window (the 3 hours prior to the DR event start time) with the average baseline consumption over the same period. Hence, the adjustment value is calculated as the difference between the actual average consumption in the Adjustment Window and the baseline average consumption for that same window (calculated as in Step 3).

5. **Final Baseline Calculation**: the final baseline consumption for the DR event period is computed as the algebraic sum of the Initial Baseline calculated in Step 3 and the adjustment calculated in Step 4.

5 Results and discussion

5.1 USN optimisation execution example

As illustrated in Figure 2, the USN receives as inputs forecasts related to PV production, energy consumption, electricity price, and feed-in tariff, as well as information about the battery, if applicable.

Assuming the optimisation is executed at midnight, and the next data has been provided as input:

- PV production forecast for the next 24 hours (kW):

```
[
0.0, 0.0, 0.0, 0.0, 0.0, 0.05, 0.3, 1.0,
1.8, 2.8, 3.5, 3.9, 4.0, 3.8, 3.3, 2.7,
2.0, 1.1, 0.5, 0.2, 0.0, 0.0, 0.0, 0.0
]
```

- Energy consumption forecast for the next 24 hours (KW):

```
[
0.4, 0.3, 0.3, 0.3, 0.5, 0.8, 1.6, 2.2,
2.5, 2.3, 2.0, 1.8, 1.6, 1.4, 1.7, 2.3,
2.8, 3.0, 3.3, 2.7, 2.3, 1.5, 1.1, 0.7
]
```

- Electricity price forecast for the next 24 hours (€/MWh):

```
[
97.06094360351562,      97.9229507446289,       97.62884521484375,
96.99246215820312,      102.53501892089844,     114.91407012939453,
133.9681854248047,      146.3689727783203,      133.84451293945312,
151.37294006347656,     148.75144958496094,     145.78756713867188,
141.54336547851562,     108.07185363769531,     111.8045425415039,
190.8706817626953,      222.40785217285156,     226.3001251220703,
216.2838897705078,      159.92906188964844,     149.29998779296875,
131.73818969726562,     122.16812133789062,     97.06094360351562
]
```

- Feeding tariff forecast for the next 24 hours (€/MWh):

```
[
55.398921966552734,     49.95810317993164,      51.97039031982422,
49.376163482666016,     45.02198028564453,      45.48946762084961,
50.729225158691406,     70.18838500976562,      73.6296310424804,
70.97499084472656,      63.21052551269531,      48.333309173583984,
39.021644592285156,     37.79984664916992,      42.7203636169433,
41.01610565185547,      53.88047790527344,      64.05542755126953,
75.23481750488281,      80.83919525146484,      78.43050384521484,
77.09212493896484,      75.572998046875,        73.89850616455078
]
```

- Battery information:
    - Capacity (kWh): 6
    - Efficiency (%): 90
    - Maximum charge/discharge power (kW): 3
    - Minimum SOC (%): 30
    - Current SOC (%): 50

Figure 13 illustrates the results for this specific USN optimisation problem. As can be seen, in the early morning, all the demand is met by purchasing energy from the grid, as PV production is scarce at these hours. Additionally, with electricity prices relatively low during this period, extra energy is purchased to charge the battery for later use. As the day progresses and PV production increases, grid dependency decreases, with demand increasingly met by discharging the battery and utilising energy from PV production. Moreover, excess PV energy is available, allowing for surplus energy to be sold back to the grid (since feed-in tariff is quite high during these hours). After midday, as PV production starts to decrease, the remaining PV output is used to charge the battery, in order to be used later when the electricity price reaches a peak. In the final hours of the day, all the demand is satisfied through a combination of grid and battery energy, maintaining the battery's minimum-security threshold of 30% capacity. Furthermore, the monetary cost of this dispatch strategy (i.e. the cost of the energy imported from the grid minus the revenue from the energy sold back to the grid) is calculated as **1.58€ for the whole day**.

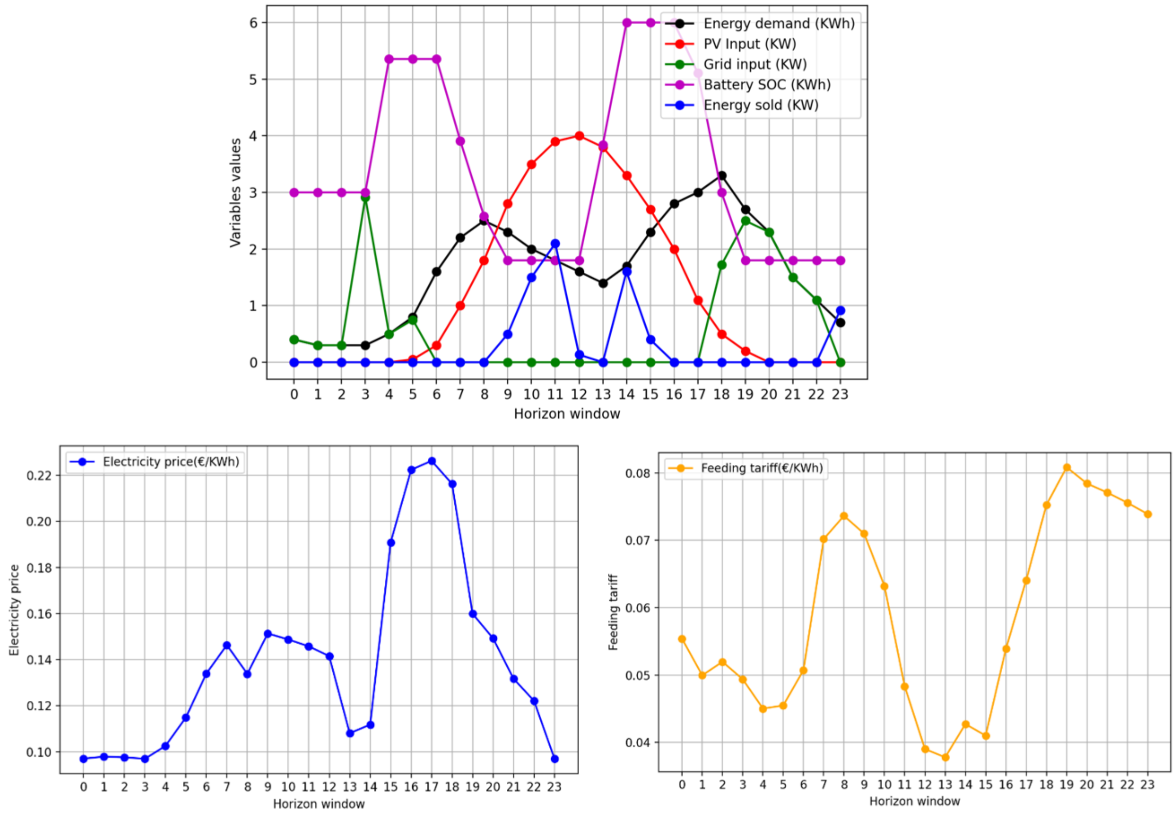

Figure 13. USN optimisation execution results (1)

On the other hand, if it is a cloudier day with less PV production, this would result in an increase in the monetary cost associated with the dispatch for that day, as more energy would need to be imported from the grid to compensate for the reduced PV production, and there would be less surplus energy available to sell back to the grid. As illustrated in Figure 14, which exemplifies this scenario, it can be observed that virtually no energy is sold back to the grid, as nearly all of it is used to meet the demand or charge the battery, even requiring the purchase of energy from the grid at certain times. These changes are reflected in the dispatch monetary cost increasing to a total of **2.22€ for the whole day**.

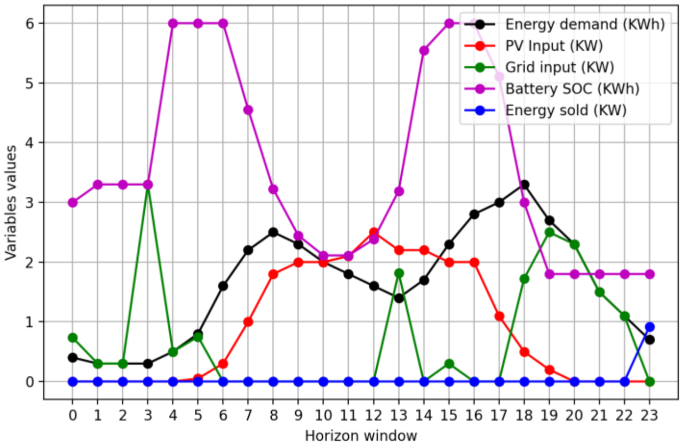

Figure 14. USN optimisation execution results (2)

Lastly, if the demand decreases as electricity prices peak, coinciding with a reduction in PV production, less energy needs to be purchased from the grid (Figure 15). Consequently, the monetary cost associated with the dispatch falls to the amount of **1.13€**.

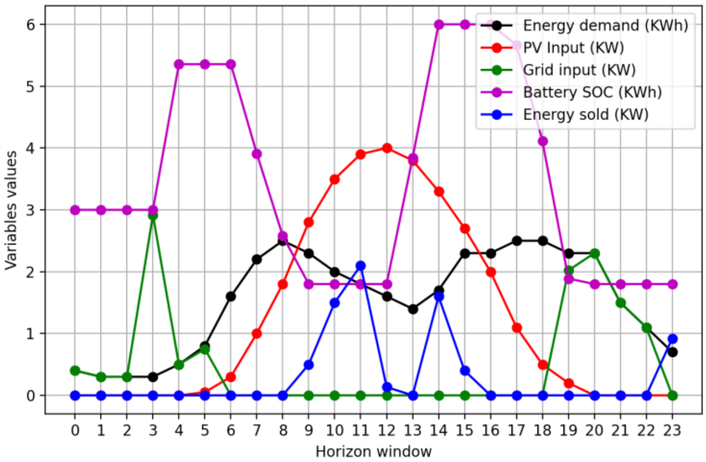

Figure 15. USN optimisation execution results (3)

These executions demonstrate that variations in the parameters such as PV production or electricity price, as well as changes in users' behaviour, directly impact dispatch costs, highlighting the pivotal role of PBDR strategies in managing costs effectively.

5.2 ASN execution example

For this execution, we will have 10 users, each of them with the specifications detailed in Table 1:

Table 1. User specifications for ASN optimisation

User	Times asked	Participation rate	Potential flexibility contribution (kWh)
User 1	12	0.92	2.35
User 2	10	0.9	1.69
User 3	9	0.33	2.29
User 4	4	0.75	2.20
User 5	0	0	1.53
User 6	5	0.4	2.54
User 7	9	0.44	0.98
User 8	1	1	0.36
User 9	10	0.4	0.76
User 10	14	0.07	0.98

After applying the Genetic Algorithm to distribute a total flexibility of **10KWh** among all the users, the following results are obtained (Table 2):

Table 2. Results of ASN distribution

User	Required flexibility (kWh)
User 1	2.35
User 2	0
User 3	0
User 4	2.20
User 5	1.53
User 6	2.54
User 7	0.98
User 8	0.36

User 9	0
User 10	0

A total flexibility of **9.96KWh** has been achieved. Additionally, if we examine the selected users, we can find that they are User 8 (who has the highest participation rate and has only been asked once), User 1 (the second-highest participation rate), Users 4, 6 and 7 (all of whom have relatively high participation rates and have not been asked excessively), and User 5 (who has not been asked until now).

On the other hand, examining the users who were not selected, we observe that they are User 2 (whose participation rate is lower than User 1’s and who has been asked more times), along with Users 3, 9, and 10 (who have the lowest participation rates and have been asked multiple times).

In this way, we can confirm that the algorithm functions as intended: achieving the required flexibility while prioritising users with high participation rates and also considering those who have been asked the least, thereby ensuring balanced opportunities for participation.

Using these results as inputs in the USN optimisation, and assuming that Figure 13 represents the energy dispatch for User 5, the USN would receive an instruction to reduce 1.53 kW at 17:00 (as can be seen in Table 2). Consequently, the USN output would be:

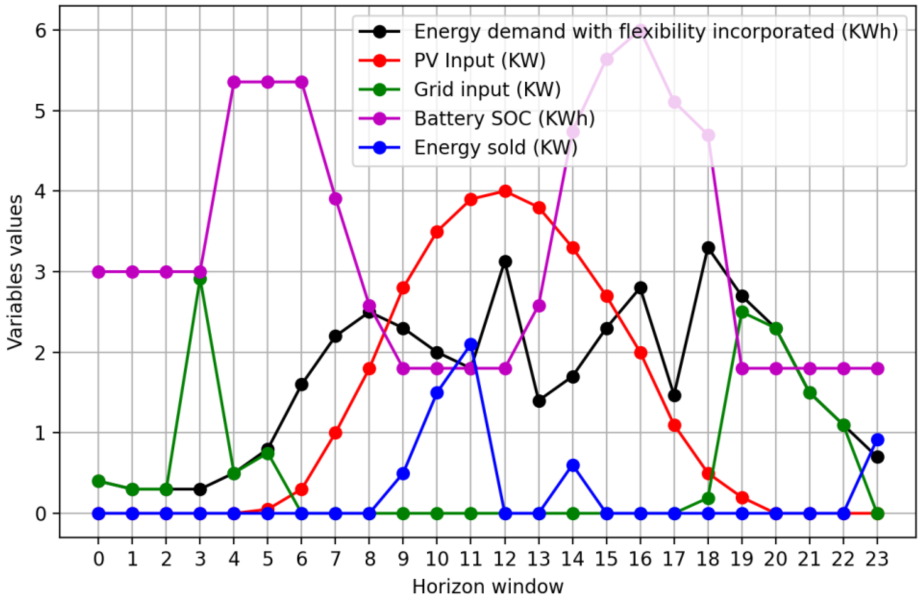

Figure 16. USN optimisation results with flexibility input from ASN

At 17:00, the demand is reduced by the amount corresponding to the flexibility value. The optimisation determines that the best time to consume this energy would be at 12:00. This adjustment in the consumption behaviour would not only provide an economic incentive (e.g., the SPOT price value of that energy or a percentage of it) by reducing energy consumption during a supply-demand imbalance period (IBDR), but it also lowers the associated daily cost from 1.58€ to **1.31€** due to the dynamic tariff (PBDR).

6 Future work

6.1 Further development

This section provides a roadmap for future lines of work essential for fully achieving DR-RISE's objectives.

- **Adoption of automatic demand response approaches.** Currently, the system operates under a manual DR approach, that is, users have complete control over switching their appliances. A fully automatic demand response will be implemented to accommodate users who wish to reduce complexity and automate the process. This approach actively engages users in flexibility provisions, minimising their required actions as a third party manages the rescheduling of appliances, thereby enhancing social acceptance. This automated framework is also beneficial for aggregators, who will no longer require highly detailed forecasts and can merely act on the appliances as needed. The adoption of automatic DR will include the modelling of heating and cooling HVAC systems, which will involve defining appropriate parameters and constraints to ensure efficient operation while minimising disruptions to end-user comfort.
- **Low-level USN control.** A lower control level should be implemented to comply with the energy dispatch determined at the USN optimisation and preserve economic benefit. This way, the USN optimisation establishes a control command that this additional control layer should track. The sampling time of this low-level control is going to be lower than an hour, resulting in several executions between two execution periods of the USN optimisation, willing to preserve whatever the USN has established. This control level will handle unexpected events and uncertainties, providing a faster response without requiring waiting for the subsequent execution of the USN module to deal with this.
- **Pilot-based continuous adaptation.** Involved users will be asked regularly about their experience and improvement suggestions throughout the pilot-testing process. Keeping this in mind, the proposed algorithms and the underlying optimisation will continuously evolve and adapt in response to user feedback, which will be collected via different ways such as workshops or our app/website.
- **Dealing with increased sampling time granularity.** Nowadays, the time granularity for the intra-day electricity market is set at 15 minutes, while the day-ahead market predominantly operates hourly. Under the EU’s Regulation 2019/943 [14], the European Union is transitioning to a 15-minute granularity for the day-ahead market, aiming to implement it across most EU countries by 2025. Consequently, to improve operations and align them with real-time conditions, the USN forecasts (PV production, consumption, electricity price, and feed-in tariff, as well as EV charging behaviour) and execution period, which were considered on an hourly basis, will be adapted to the 15 minutes determined by the EU’s Regulation.
- **Adaptation to regulatory changes.** The previous bullet point is a representative example of how DR-RISE’s optimisation strategies should adapt to possible variations in energy regulation across Europe. Accordingly, the algorithms included in this report will be modified per legislative developments. For example, a DR-RISE pilot is conducted in Greece, where dynamic electricity tariffs are set to expand by 2025. This context-specific

adaptation ensures that DR-RISE remains reactive to evolving market structures and regulatory frameworks.

6.2 Research avenues

In what follows, potential research avenues that could be explored beyond the scope of the project's specification are presented.

- **Sensitivity analysis of the prediction horizon.** Undoubtedly, selecting the prediction horizon in MPC strategies is an imperative aspect of such approaches. A long prediction horizon can result in better anticipation of the system's behaviour; however, a very long horizon could be very conservative, introducing noise in the predictions, resulting in lower accuracy. On the other hand, a short horizon results in a controller capable of dealing with sudden changes, such as uncertainties. However, if it is too short, it may not be capturing long-term dynamics. Hence, the selection of the horizon directly affects the optimisation performance, besides directly affecting the computational effort due to the number of variables handled along the entire sequence. For these reasons, it would be interesting to study the behaviour of our optimisation in response to variations of the prediction horizon.
- **Stochastic uncertainty.** Dealing with unknown parameters is also a crucial aspect directly affecting the optimisation's performance. To this end, an artificial intelligence-based forecasting module is implemented to receive the predictions of the unknown parameters of the USN, namely the PV production, consumption, electricity price and feed-in tariff, and the EV charging behaviour. However, it would be interesting to study a scenario-based approach in which the different possible realisations of the disturbance are probabilistically considered. That is, different scenarios are studied, and each scenario is assigned a probability of occurrence to examine uncertainties more thoroughly.

7 Conclusion

The main goal of the optimisation is tackled using an architecture based on Smart Nodes, which are pivotal for building functional distributed energy grids. These modular smart nodes comprise the necessary tools to optimise and manage energy flows. In this regard, the optimisation has been broadly divided into two levels, the User Smart Node (USN) and the Aggregator Smart Node (ASN), which will differ in both logic and the scope of application.

At the USN level, energy dispatch for every household is optimally managed considering electricity price, energy consumption, and, where appropriate, availability of energy storage systems (ESS) and energy production. Additionally, users managed at the USN level will be notified about DR events from the ASN so they can act accordingly. For this purpose, the maximum flexibility of a user is defined per asset capable of performing DR, such as HVAC and shiftable appliances. A model predictive-based optimisation will determine the amount of energy consumption from the distinct available sources—including the grid, battery, and, if applicable, PV panels—to meet the requested demand and will identify the energy that should be stored or traded back to the grid.

At a higher level, the ASN performs a heuristic optimisation to schedule the demand-response events and distribute them among the available households. This smart node sets the flexibility events that users should follow to comply with market requests and trades based on the aggregated flexibility of the corresponding households. Once the DR event is over, the ASN will use the historical baseline to justify the flexibility provided. If the user's consumption is lower than the baseline, the user will be rewarded for that energy supplied.

The next steps of DR-RISE’s optimisation module are detailed in Section 6.1 of this deliverable, where adoption of automatic demand response, adaptation to user feedback and regulatory changes, and consideration of a lower control level to preserve the economic benefit of end-users are planned.

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