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New business models for innovative energy services bundles for residential consumers

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Coordinator	CIRCE – Fundacion Circe Centro de Investigacion de Recursos y Consumos Energeticos
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Deliverable D5.1
Monitoring, forecasting,energy management analytics, flexibility analytics and optimisation mechanisms

Deliverable number	D5.1
Deliverable name	Monitoring, forecasting,energy management analytics, flexibility analytics and optimisation mechanisms
Lead beneficiary	UBITECH
Description	Description of the algorithms for monitoring, forecasting,energy management analytics, flexibility analytics and optimisation mechanisms. It includes proposed outputs for the visualisation toolkit.
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Related task(s)	T5.1,T5.2,T5.3
Type	Report
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Main author	Dimitra Georgakaki (UBITECH).
Contributors	Juan Antonio Aranda Uson (CIRCE),Roberto Lázaro (CIRCE), Leon Nielsen (CIRCE), Alejandro Martín (CARTIF), Víctor Serna (CARTIF), Álvaro Samperio (CARTIF).

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V3 – Final deliverable submission	21.12.2021	Minor	CIRCE

TABLE OF CONTENT

ABBREVIATIONS

Abbreviation	Name
API	Application Programming Interfaces
DER	Distributed Energy Resource
DHW	Domestic Hot Water
DOD	Depth of Discharge
EE	Energy efficiency and self-consumption optimisation services
FL	Flexibility services
GDM	Global Demand Manager
GUI	Graphical User Interface
HVAC	Heating Ventilation and Air Conditioning
LDM	Local Demand Manager
MIP	Mixed-Integer Programming
NE	Non-energy services
PV	Photovoltaic
RT	Sensoring and smart equipment retrofitting
SMS	Short Message Service
SOC	State of charge
SRI	Smart Readiness Indicator
WP	Work package
SOH	State of Health
EV	Electric Vehicle
ESCO	Energy Service Company

UC	Use Case
KPI	Key Performance Indicator
LPP	Linear Programming Problem
EMS	Energy Management System
VPP	Virtual Power Plant
DR	Demand Response

1 INTRODUCTION AND OBJECTIVES

One of the main objectives of the frESCO project is the development of novel energy services that ESCOs and Aggregators can offer to building owners and users. Four main groups of services have been identified throughout the project: Sensoring and smart equipment retrofitting (RT), Energy efficiency and self-consumption optimisation services (EE), Flexibility services (FL) and Non-energy services (NE). All of them help to increase the Smart Readiness Indicator (SRI) of buildings, as they empower users when it comes to managing and getting informed about their energy usage.

In order to develop and test all frESCO features, a complete platform architecture has been designed (see Figure 1). There are two components in the users' side, the Local Demand Manager (LDM), which is focused in consumers/prosumers, and the Global Demand Manager (GDM), design to help ESCOs and aggregators.

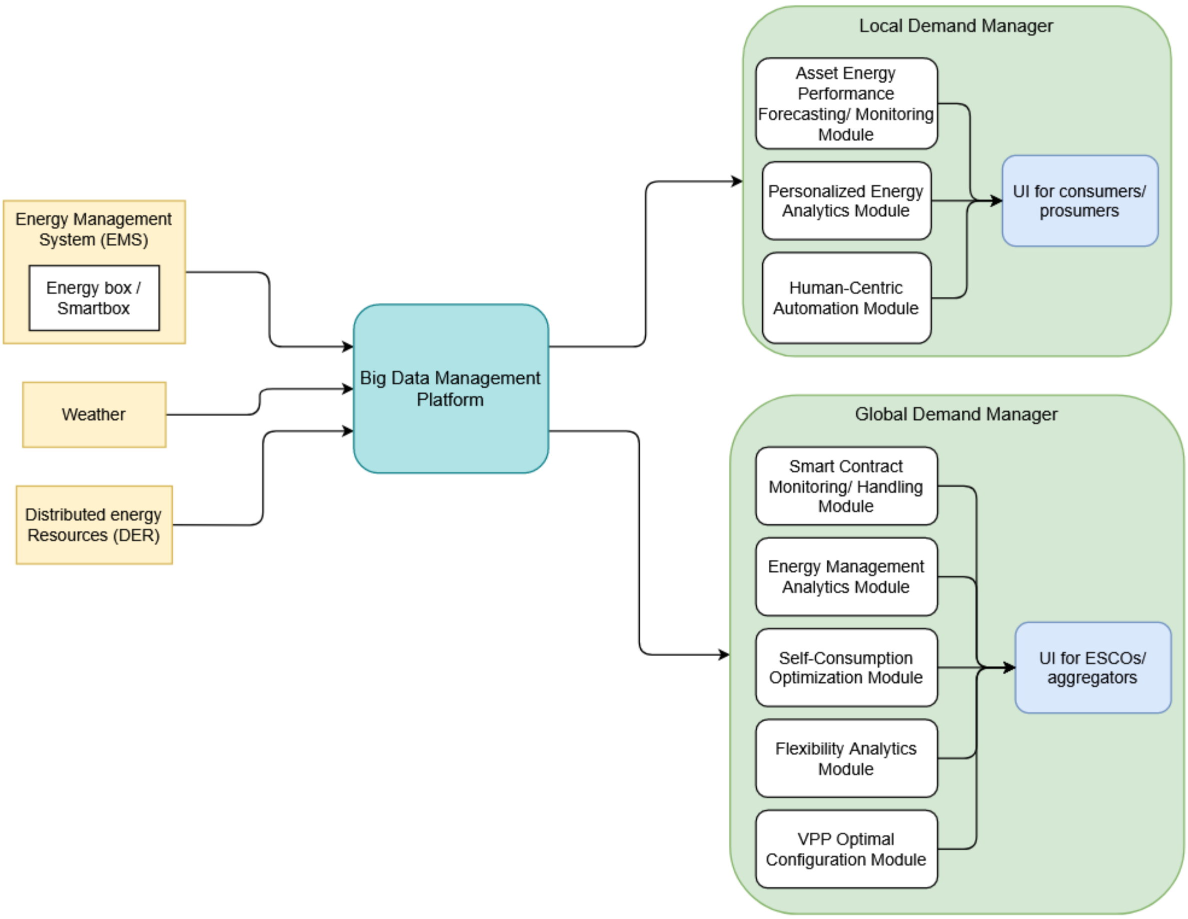


Figure 1. frESCO platform architecture (D2.5)

1.1 Deliverable objectives and scope

This report is the first outcome of the work being done in *task 5.1 Advanced Performance Monitoring/ Forecasting Module for Generation/ Storage/ Demand Assets*, task 5.2 Energy Management Analytics and Self-Consumption Optimization Tool and task 5.3 Advanced Flexibility Analytics and Optimal VPP configuration tool for explicit demand response optimization that considers the consumer.which are three of the five tasks in *WP5 – Multi-service package toolkit for service providers*.

The objective of this deliverable is to introduce the algorithmic functionality of the Asset Energy Performance Forecasting/Monitoring Module (part of the LDM component), the Energy Management Analytics Module, the Self-Consumption Optimization Module, the Flexibility Analytics Module and the VPP Optimal Configuration Module (all part of the GDM component)

1.2 Relationship with other tasks

D5.1 is related to other deliverables, tasks and WPs, further explained in Table 1.

Table 1. Relation to other deliverables, tasks and WPs

Deliverable/ Task	Title	Comment
D2.5 / T2.5	Report on the frESCO conceptual architecture / Specifications, Architecture Design and Communication Interfaces	D2.5 / T2.5 introduced the whole fresco platform structure, which includes T5.1, T5.2 and T5.3 modules
D3.1 / T3.1	Definition / Design of the novel energy services for residential consumers	All the services of the fresco project have been design in D3.1 / T3.1
D4.4/T4.4	Personal and Enterprise Big Data and Edge Analytics Algorithms Definition as a baseline for advanced energy service bundles	The Big Data Platform will provide all the business applications of WP5 with the baseline descriptive and predictive analytics regarding consumer energy behaviour, user comfort preferences, user flexibility profile etc.

D5.1/T5.1	Advanced Performance Monitoring/Forecasting Module for Generation/ Storage/ Demand Assets	The module Asset Energy Performance Forecasting/ Monitoring Module, which is developed in T5.1. It is on monitoring and forecasting at dwelling level. It will provide generation and demand forecasting on a long term basis to users through the visualisation toolkit, and a baseline tool for efficiency PMV.
D5.1/T5.2	Energy Management Analytics and Self-Consumption Optimization Tool	This tool will use short-term forecasts of energy consumption, energy generation and energy storage (where applicable) in order to provide ESCOs with self-consumption optimisation scenarios. Also, advanced clustering methods will provide ESCOs with useful insights in order to gain better knowledge on their consumers/prosumers.
D5.1/T5.3	Advanced Flexibility Analytics and Optimal VPP configuration tool for explicit demand response optimization that considers the consumer	This tool will use the users' flexibility profiles and available assets/DR attributes according to the predefined smart contract signed with the aggregator, to optimise their portfolio to the path of maximum available flexibility at a given DR event. Also, advanced clustering methods will provide Aggregators with useful insights in order to gain better knowledge on their consumers/prosumers.
D5.4/T5.4	Release of the Human-Centric automation module	The flexibility signals from T5.3 will be dispatched to each user through the Human-Centric automation module (T5.4).

D5.5/T5.5	Blockchain-enabled Smart Contract Monitoring, Handling, Settlement and Remuneration	The smart contract parameters will be sent to the Flexibility Analytics Module (T5.3).
D5.1/T5.1-T5.2	Advanced Performance Monitoring/Forecasting Module for Generation/ Storage/ Demand Assets Energy Management Analytics and Self-Consumption Optimization Tool	Results will be generated in terms of energy management and optimisation for prosumers and groups of prosumers. This optimisation will consider renewable generation, manageable and non-manageable demands, storage systems, electric vehicles, electric energy prices and deviation penalties. One of the resulting outputs of this additional work, merging both tasks, will be the conclusions from the optimization test bench.

As next steps, in Delivable 5.2 the algorithms will be developed in a beta version and outputs and monitoring KPIs will be defined for implementation in the corresponding visualisation toolkits . Finally, the tools created will be tested at each demo site of the project in WP6.

1.3 Document Structure

Each section of this document (sections 2-4) aims to cover the description of algorithms and proposed dashboards with relevant users, for each of the tasks 5.1, 5.2 and 5.3. More specifically section 2 (task 5.1) is about the monitoring and forecasting services regarding energy generation/storage/demand at a building and asset level. Section 3 (task 5.2) covers the energy efficiency analytics and the optimisation process regarding self-consumption from the ESCOs point of interest. Finally section 4 (task 5.3) covers the flexibility analytics and the optimisation process of the prosumers’ flexibility behavior configured as VPPs. General conclusions are given in section 5.

2 MONITORING AND FORECASTING SERVICES FOR ENERGY GENERATION/STORAGE/DEMAND ASSETS

2.1 Introduction and Requirements overview based on frESCO Use Cases

"Advanced Performance Monitoring/ Forecasting Module for Generation/ Storage/ Demand Assets" describes the set of functionalities delivered under the Asset "Energy Performance Forecasting/ Monitoring Module" of the Local Demand Manager, as already presented in the frESCO architecture. The objective is to provide building users with the required information to understand generation and demand evolution in their home and forecast generation and demand in the mid and long term. These forecasts will be a valuable insight to understand the effect of energy efficiency decisions in the long term.

Firstly, data are accumulated and stored in the Big Data Platform's Data Storage Module. Later, the data of demand and generation at the dwelling level (mainly metering data) and other related variables (such as internal and external temperatures, local irradiation, etc.) will provide the information to the generation of forecasting models on mid-term/long-term time windows and for monitoring the use of the energy in the dwelling.

From the user's point of view, the combination of monitoring and forecasting on the same tool will provide the user with the necessary information for a correct understanding of the home's energy situation. It will provide present and future tracking of the generation and demand and historical behavioural trends. In addition, it will provide knowledge about the impact of the user's decisions on the final energy balance of the house (consumption-generation).

The specific requirements that we are going to address are those of D2.5 and are presented in the following tables:

Table 2. Functional and non functional requirements and their relationship with the relevant WP and UC

Req_014	The system shall provide near real time monitoring of energy demand, generation, and consumption at dwelling level.	WP5	UC.01, UC.02, UC.03, UC.04, UC.05
Req_026	The system shall provide forecasts of energy demands and generations (mid-term and long-term) at dwelling level.	WP5	UC.05

Req_049	The system shall increase the user awareness regarding EE and flexibility patterns through an informative user interface.	WP5	UC.04

Table 3. End user requirements and their relationship with the relevant WP and UC

Req_002	The system shall allow near-real-time monitoring of the energy consumption and performance and their visualisation for ESCOs and consumers/prosumers.	WP4, WP5	UC.03, UC.04
Req_006	The system shall provide forecasting tools for energy efficiency assessment and verification.	WP3, WP5	UC.04
Req_014	The system shall support the provision of billing monthly reports.	WP5	UC.03

2.2 Monitoring and forecasting algorithm specifications

In this section, the Monitoring and forecasting services algorithms specifications are described. Data needs, methodology and expected outputs are explained for the main objectives of task 5.1 Monitoring and forecast of generation and demand at dwelling level.

2.2.1 Input data and technology stack

In this section, a list of needed variables and information is provided to satisfy the task 5.1 objective.

- Building Energy generation (PV, others if applicable) (kWh, time series)
- Building Energy consumption (kWh, time series)
- External Ambient Temperature (ºC, time series)
- Irradiation (W/m2, time series)
- HVAC setpoint (°C, fixed value)
- DHW setpoint (°C, fixed value)
- Indoor temperature (°C, time series)
- DHW tank water temperature (°C, time series)
- HVAC Energy consumption (kWh, time series)
- DHW energy consumption (kWh, time series)
- EV energy consumption (kWh, time series)
- Occupancy (boolean (1-0), time series)

- Power (kW, fixed value) time (min, fixed value) and time sections (fixed value) required by each electric device to work (e.g. device 1 requires 2 kW during 60 minutes each Friday).
- Batteries capacity (kWh, time series), SOC (%kWh, time series), SOH (%, time series) and nominal charge and discharge power (kW, fixed value).
- Ambient temperature forecast (°C, time series).
- Irradiation forecast (W/m2, time series)
- Other electric energy consumption (kWh, time series).
- static properties PV: nominal power, number of modules, modules datasheet…
- static properties HVAC: nominal power output, efficiency
- static properties DHW: water tank volume capacity, nominal power output
- static properties of EV (ev_capacity, ev_charge_rate, ev_soc_max, ev_soc_min)

The data resolution in case of time series will be hourly, preferably.

About the technology stack, the architecture proposed[1] to interact with the big data platform and the UI in the LDM follows a schema similar to the following:

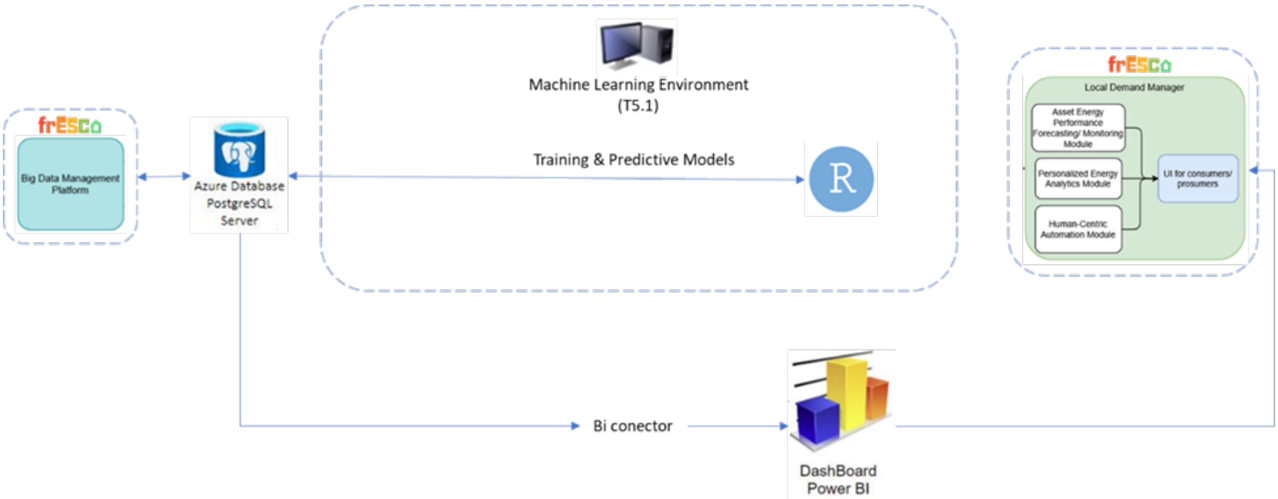


Figure 2. Proposed Architecture machine learning environment

[1] At this stage of the project, valuable information has to be defined, such as interaction with the Big Data platform or UI integration in the Local demand manager. Therefore, this proposed architecture could be modified or optimised depending on the system performance.

On this architecture, a Machine learning environment is defined. It includes:

- Database: It stores the input data of models and writes the outputs of the algorithms. This database will feed the Big data platform with the results and the visualisation toolkit. In the example, an Azure Database for PostgreSQL is proposed.
- Dashboard environment. It will show the main results of the algorithms, and it will be connected to the UI. In the example, the Power Bi tool is proposed.
- Machine learning models: In the example, the models will be generated in R programming. It will run on a machine whose specifications will be scaled to the data and modelling requirements.

This module will be deployed on the cloud if possible. It is going to be delivered as a web-based environment. Analytics will be run on the cloud on a virtual machine . The proposed tech stack is as follows:

- Backend: Power Bi Service (back-end)
- Frontend: Power Bi service (front-end web (WFE)) (and other valuable services like Power Automate)
- Databases: Azure Database for PostgreSQL
- Analytics: R and Python programming and respective libraries like Keras, reticulate, Tensorflow
- Virtual machine: Windows virtual machine for Azure (E.g. D2as v5, D4as v5)

2.2.2 Algorithms for demand and generation monitoring at dwelling level

2.2.2.1 Objective

The main objective of this section is to define the calculations and outputs focused on providing the prosumer with a general view of the dwelling in terms of generation and demand.

A performance monitoring module will be designed to extract different demand and generation curves patterns.

Due to the prosumer's consumption behaviour and the nature of solar energy, demand and solar electricity generation, their corresponding time series have hourly, daily, weekly, monthly and seasonal components. Therefore, to consider the seasonality of generation and demand, a decomposable time series model will be used and later applied in the forecasting module (additive and multiplicative models will be assessed). This will provide valuable insights to users about the overall energy generation and consumption trends.

2.2.2.2 Methodology

The main calculations are based on different aggregated values of the main variables of interest for the prosumers. From historical data to the final results, the data will be filtered, classified and aggregated to provide a holistic information panel to the prosumer.

Data classification:

- Demand curve under specific working conditions
- Generation curve under specific working conditions

Data aggregation from historical data: It affects variables of interest to be monitored, such as generation, Demand, Ambient Temperature, Indoor temperature, setpoint indoor temperature, setpoint tank water temperature. The data will be aggregated:

- Hourly
- Daily
- Monthly
- Seasonal (summer, winter, by working conditions)

Decomposable time series model. These models can extract trends and forecasts described in section 2.2.3. In this case, they can be considered as:

- Generation trends from previous historical data.
- Demand trends from last historical data: to catch influencing behaviours of prosumers.

2.2.2.3 Expected outputs

- Historical comparison
  - Aggregated figures (daily, monthly, yearly)
  - Generation and Demand curves calculation
- Extract recurring patterns in terms of generation and demand
- Main metrics:
  - Sum of generation at dwelling level
  - Sum of consumption at dwelling level

- % Coverage generation/demand: sum of generation in study period related to the demand in the study period
- % excess of Energy from PV once demand is covered
- Cumulated generation/demand: cumulative energy from the first data stored in the database

2.2.3 Algorithms for long term demand and generation forecasting at dwelling level

2.2.3.1 Objective

The main objective of this section is to define the calculations, models, and outputs focused on providing the prosumer with a general view of the dwelling in terms of generation and demand forecasting. It will help prosumers to understand better the effects of efficient actions.

2.2.3.2 Methodology

The main calculations and the expected models to be applied are defined in this section:

- Mid-term and long-term demand and generation forecast. Models considered in this module can be additive or multiplicative. The expected models to be tested are :
  - Seasonal Autoregressive Moving Average (SARIMA) [1]. It is a multiplicative method that incorporates stationary and non-stationary variations.
  - Forecasting at scale [2]. It is used for social media user data statistics. Among the advantages of this technique is its flexibility when data has several seasonal patterns.
  - K-neighbours method (Knn) [3]. These models evaluate the distance between independent variables. Later, the K nearest observations are chosen, and the combination of their response is used to estimate the next value of the objective variable.
  - Seasonal-Trend Decomposition Algorithm MSTL [4]. It is an extension of the traditional STL procedure. It allows the time series decomposition where multiple seasonal patterns are expected.
  - Monthly forecasting can be achieved by applying the models cited before. They can provide forecasts from short term to long term and can consider seasonality.

- Parallel forecasting based on actual data following the activation of EE services. It provides the opportunity to monitor the performance of user actuation.
    - Multivariate models ANN [5] from exogenous predictor variables (Ambient temperature, setpoint temperature, expected radiation, etc.). These models will be tuned as a regressive model where the objective variable is the generation or demand. The effect of variations on predictor variables over the objective variable could be estimated in this way.

2.2.3.3 Expected outputs

The expected results provided on this module in terms of mid and long term forecast are:

- Monthly forecasts from historical data of generation (Actual trend)
- Monthly forecasts from historical data of Demand (Actual trend)
- Monthly forecasts of the generation in simulated working conditions (e.g., forecast when Ambient average temperature is 30°C, monthly production in summer/winter conditions).
- Monthly forecasts of demand in simulated working conditions (e.g., forecast when HVAC setpoint is 19°C, demand in summer/winter conditions)
- Other KPIs:
    - Expected impact on energy (production or demand) from expected simulated conditions [%]: It is the expected impact measured in % from expected simulated conditions. This KPI measures the consequences of applying an efficient decision (like reducing setpoint temperature) in a mid and long term time horizon.
    - Expected impact on energy (production or demand) from expected simulated conditions [kWh]: It is the expected impact measured in kWh from expected simulated conditions. In this case, a negative value means saving energy due to an efficient decision.

2.2.4 Relationship with other frESCO modules

The Asset Energy Performance Forecasting/Monitoring Module, Personalized Energy Analytics Module and Human Centric Automation Module are part of the **Local Demand Manager** (LDM) component.

"Energy Performance Forecasting/Monitoring Module" takes the data inputs from the **Big Data Management Platform** where all user data are stored. After data processing, the results will be stored in the cloud. The module will communicate with the final users through a **UI for consumers/prosumers** (GUI), which summarises all the LDM information.

2.3 Monitoring and Forecasting services visualisation mockups

2.3.1 Information sharing with end-users

The Local Demand Manager (LDM) is the platform in communication with the final user in the dwelling. LDM has different mechanisms to facilitate this communication with the user. In this case, the selected method is by a Graphical User Interface (GUI), which is web-based. This GUI will provide users with valuable information about the dwelling in a friendly and interactive way.

The outputs from task 5.1 will be stored in the platform, and KPIs and related valuable info for users will be shown in the GUI available in the visualisation toolkit by different dashboards (collected and assembled in task 5.4).

This GUI will show the expected results of the module in a user-friendly environment. A proposal of the dashboards related to the module "Asset Energy Performance Forecasting/Monitoring Module" is described in the following sections

2.3.2 Proposed Dashboards

In this section, the following dashboards are proposed:

- **Monitoring Demand/Generation Dashboard (historical data)**

This dashboard allows the user to monitor generation and demand. It is based on historical data and shows aggregated values and averaged daily curves to be compared.

Figure 3. Monitoring Demand/Generation Dashboard from historical data

1. Analysis selection: allows the user the choice of generation or demand
2. Study period selection: user can select the period of study
3. Cumulative [kWh]: cumulative energy from the first data stored in the database
4. Study period [kWh]: sum of energy in the study period
5. Coverage demand [%]: is the sum of generation in study period related to the demand in the study period.

$$\text{Coverage demand [\%]} = \frac{generation\ study\ period}{demand\ study\ period} * 100$$

6. Excess generation [kWh]: excess of energy from generation source once it has satisfied the demand.
7. Aggregated values (graph): this graph shows aggregated values of energy. The possible selection of aggregations is Hourly, Daily or Monthly. This graph can include time series decomposition to catch seasonality.
8. Aggregated values (table): this table shows aggregated values of generation and demand. The possible selection of aggregations is Hourly, Daily or Monthly.
9. Daily curves Averaged (graphs): this graph shows the average daily curve of generation or demand of the selected period. This curve can be compared to different scenarios

(winter, summer or a custom scenario defined by ranges of several influencing variables. This graphical tool can include pattern recognition, which could be included as a list of different typical daily curves detected in the dwelling.

10. Daily curves Averaged (table): this table shows the average daily curve of generation or demand of the selected period and the curves in different scenarios.
11. Scenario selection: this selector allows selection of the scenarios of comparison in the averaged daily curves.
12. Customise scenario: this panel allows definition of a custom scenario to be compared. To define the scenario, the user has to specify ranges of analysis in different variables of interest.

- **Monitoring Demand/Generation Dashboard (Forecast Data):**

This dashboard allows the user to forecast generation and demand mid and long-term (monthly resolution). Learning of models is based on historical data. It shows the forecast from real historical data and a customised scenario. In this way, it is possible to measure the future impact of efficiency decisions.

Figure 4. Monitoring Demand/Generation Dashboard (Forecasted Data):

1. Analysis selection: allows the user the choice of generation or demand
2. Learning period: this selector enables the definition of the considered period for forecasting model learning. By default from the last year.
3. Forecasts month ahead: this input box allows users to define the months to be forecasted.
4. Forecast from historical data: this graph shows the observed and forecasted monthly values from historical data.
5. Historical data + Forecast: this table shows the monthly data related to the graph "Forecast from Historical data"
6. From Historical Scenario [kWh]: It is the value of energy expected in the forecasted period from historical data.

7. Forecast from customised scenario data: this graph shows the observed and forecasted monthly values from a customised data scenario.
8. Customised data scenario + forecast: this table shows the monthly data related to the graph "Forecast from customised scenario data".
9. From customised scenario [kWh]: The value of energy expected in the forecasted period from the customised scenario.
10. Customise scenario: this panel allows to define the custom forecasted scenario to be compared. To define the scenario, the user has to specify average values for different variables of interest.
11. Expected impact [%]: It is the expected impact measured in % from expected simulated conditions. This KPI measures the consequences of applying an efficient decision (like reducing setpoint temperature) in a mid and long term time horizon.

$$\text{Expected Impact [\%]} = \frac{\left|Forecast_{from\ Custom} - Forecast_{from\ Historical}\right|}{Forecast_{from\ Historical}} * 100$$

12. Expected impact [kWh]: It is the expected impact measured in kWh from expected simulated conditions. In this case, a negative value means a saving in energy due to an efficient decision.

$$\text{Expected Impact [\%kWh]} = Forecast_{from\ Custom} - Forecast_{from\ Historical}$$

3 ENERGY MANAGEMENT ANALYTICS SERVICES AND SELF-CONSUMPTION OPTIMISATION

3.1 Introduction and Requirements overview based on frESCO Use Cases

Energy Efficiency (EE) services in fresco aim to benefit consumers, prosumers and ESCOs and will try to create novel business models (prosumer-oriented business models) like the self-consumption as a service model. Such a service promotes energy self-sufficiency, through the use of DERs (PV, battery, EV, HVAC etc.) by exploiting as much as possible the power generated on the building (maximising the self-consumption) and minimising the excess of energy given back to the grid. By adopting this energy usage behaviour, the prosumer maximises energy savings and minimises energy cost savings. On the other hand, the ESCOs by performing aggregated energy analytics on their portfolio, have the opportunity to gain useful insights on the road to new business models and improve existing ones for their customers.

The self-consumption scenarios that are applicable to each building are highly dependent on the asset availability and type. We can divide them into two categories: energy storage scenarios and load-shifting scenarios. More details are provided in the next section. The specific requirements that we are going to address are those of D2.5 and are presented in the following table:

***Table 4. Requirements** relevant to the EE services from the ESCOs point of interest and their relationship with the relevant WP and UC.*

Req_001	The system shall have access to DER management system data.	WP4, WP6	UC.01, UC.02
Req_002	The system shall have access to EMS data.	WP4, WP6	UC.01, UC.02
Req_003	The system shall provide the possibility for the ingestion of real-time data assets.	WP4, WP6	UC.01, UC.02
Req_004	The system should have access to weather data.	WP4	UC.01
Req_007	The system should provide the possibility to a user to upload data files (i.e. csv, json, xml, etc.) or schedule future data asset uploads.	WP4	UC.01
Req_013	The system shall provide near real time monitoring of energy demand, generation, and consumption at dwelling level.	WP5	UC.01, UC.02, UC.03, UC.04, UC.05
Req_018	The system shall allow the energy service providers to perform consumers portfolio segmentation /clustering according to different parameters.	WP4, WP5	UC.03, UC.05, UC.08

Req_024	The system shall provide forecasts of energy consumption trends.	WP4, WP5	UC.03, UC.04, UC.05
Req_025	The system shall provide forecasts of energy demands and generations (mid-term and long-term) at dwelling level.	WP5	UC.05
Req_026	The system shall provide the possibility for short-term (day-ahead) energy demand forecast.	WP4	UC.05
Req_027	The system shall provide short-term weather forecast.	WP4	UC.04, UC.05
Req_028	The system should maximise the self-consumption considering all dynamic and static parameters involved and without compromising optimum overall energy usage .	WP5	UC.05
Req_028	The system should maximise the self-consumption considering all dynamic and static parameters involved and without compromising optimum overall energy usage .	WP5	UC.05
Req_047	The system shall provide visualisation of EE/flexibility information at consumer level through a user interface.	WP5	UC.04, UC.05, UC.07

3.2 Energy management analytics and self-consumption algorithms specifications

3.2.1 Input data and technology stack

The Energy Management Analytics Module and the Self-consumption Optimization Module that reside in the Global Demand Manager, take input from the Big Data Management Platform, where all the available sensor, market and user data are stored. Any identified strategies for ESCOs that come as results from the Energy Efficiency Analytics, will be targeted to their respective consumers, so an interaction with the Personalised Energy Analytics Module is necessary, always via the Big Data Management Platform. Input data needed are:

Sensor Data

- PV Energy Generation (kWh, time series)
- Building Energy Consumption (kWh, time series)
- Building Energy Storage (kWh, time series)
- External Ambient Temperature (ºC, time series)
- Indoor temperature (ºC, time series)
- HVAC Energy consumption (kWh, time series)

- DHW energy consumption (kWh, time series)
- EV energy consumption (kWh, time series)
- static properties of battery (battery_capacity , battery_charge_rate, battery_soc_max, battery_soc_min)
- static properties PV: nominal power, number of modules, modules datasheet
- static properties HVAC: nominal power output, efficiency
- static properties DHW: water tank volume capacity, nominal power output
- static properties of EV (ev_capacity, ev_charge_rate, ev_soc_max, ev_soc_min)

User Data

- Thermal, visual and air quality comfort profile

The Energy Management Analytics Module and the Self-consumption Optimization Module are going to be delivered as a web-based application with the following tech stack:

- Backend: Django framework
- Frontend: Angular framework
- Databases: Postgres, Elasticsearch
- Analytics: Python and respective libraries like Pandas, Sklearn
- Deployment: Kubernetes

3.2.2 Algorithms for energy management analytics for ESCOs

The ESCOs are particularly interested in aggregated analytics at building level and at user portfolio level. The KPIs of interest are usually around energy generation, energy consumption at building and at device level, self-consumption rate, energy and cost savings. Comparative analytics provide useful insights to the ESCOs as they can compare energy performances of different buildings regarding the self-consumption and derive the optimal hours for better exploiting energy generation peaks at each building.

Another interesting feature that we will investigate here is finding and comparing similar peers regarding the energy generation and consumption. Because of the fact that similar peers (peers that belong to the same cluster e.g. with low/mid/high energy consumption profiles) can be found either at a single-building level or at an inter-building level, for the case of multiple similar buildings like the demo of Krk Island, a two-level K-means clustering will be designed and implemented. More specifically, in the Single-building K-means profiling, the K-means clustering is applied to cluster the daily load profiles. The centroids of each cluster are extracted as the representative profiles of the source buildings. Then in the Inter-building K-means clustering, all the representative profiles are aggregated together to run inter-building clustering and identify the typical profiles of all buildings belonging in the ESCOs portfolio.

3.2.3 Algorithms for self-consumption optimisation for ESCOs

The optimisation process that we are going to follow is the standard methodology as described in the PuLP Python library, which we will use for solving our Linear Programming Problem (LPP):

- Define the problem
- Collect data and develop a Python model
- Solve with PuLP
- Validate solution: accept solution and go to implementation or decline solution and modify model

The definition of the problem can be further broken down into 4 key steps:

- Identification of the Decision Variables: Unknown quantities that represent the output of the LPP solution
- Formulation of the Objective Function: Maximisation or minimisation function that aims to evaluate the factor by which each decision variable would contribute to a value representing cost, profit etc.
- Formulation of the Constraints: Equations that describe the restrictions or limitations on the decision variables
- Identification of data needed for the Objective Function and Constraints

The self-consumption optimisation module that resides in the Global Demand Manager can deliver the following indicative scenarios for the end-user, i.e. the ESCOs:

Minimise the energy cost using energy stored in the battery

The first scenario that we deal with is the dissemination of produced energy in a such way that the cost of the energy bill will be minimised. The optimisation solver Identifies peaks in energy grid price and can notify the user to use his battery at those slots. Additional notifications are sent when grid price is low for charging the battery. In this version of the deliverable we are not taking into account automation control actions, which will be further analysed in a future version. Although the hybrid inverter on which the battery is attached carries a dedicated software where its default operational mode is indeed the self-consumption mode, we are capable of overriding this setting by switching to manual mode so that the solver can run and provide automation in the battery control (which adds even more value than the notifications mentioned in the beginning).

The objective function of the optimisation process takes into account the electricity cost on an hourly basis. Here, it is considered that buildings can only buy electricity from the grid as we are targeting the minimisation of the cost by optimising our self-consumption plan, rather than by selling energy back to the grid. The objective function equation is the following:

$$\min \sum_{i}^{T} C_{buy}\, P_{grid(t)} \tag{1}$$

where C_{buy} is the wholesale market electricity price of each demo country and $P_{grid}(t)$ is the power imported from the grid at each timeslot.

The energy balance restrictions for each timeslot are expressed with the following equations:

$$E_{pv_i} = E_{pv-load_i} + E_{pv-bat_i} + E_{surp_i} \tag{2}$$

$$E_{load_i} = E_{pv-load_i} + E_{bat-load_i} + E_{grid-load_i} \tag{3}$$

$$E_{soc_i} = E_{soc_{i,0}} + E_{pv-bat_i} - E_{bat-load_i} \tag{4}$$

where E_{pv} is the energy produced by the PV, $E_{pv\text{-}load}$ is the energy directed from the PV to the loads, $E_{pv\text{-}bat}$ is the amount of energy directed into the battery and E_{surp} is any redundant amount of energy that was not possible to be self-consumed. E_{load} refers to the total amount of energy consumed, $E_{bat\text{-}load}$ is the amount of energy directed from the battery to the loads and $E_{grid\text{-}load}$ Energy from the grid directed to the loads. Finally, E_{soc} stands for the total energy stored in the battery at a given time, whereas $E_{SOC,0}$ is the minimum state of charge.

The data needed for the Objective Function and Constraints are the day-ahead forecasted energy produced, energy consumed and grid electricity prices, as well as the battery charge rate, battery capacity and battery soc min/max.

Maximise the energy for ev charging using energy produced at PV peak

The purpose of the optimisation solver in this case is to exploit the flexibility of the ev charging in order to maximise pv self-consumption and minimize the energy bought by the grid. The user will be notified when available timeslots are found. Again here, we do not examine automated ev charging which can be an extended scenario for a future enhancement in the solver.

The objective function maximises the energy that the ev battery is receiving by the pv panel while minimising the energy received by the grid. This can be described by the following equation:

$$\max \sum_{i}^{T} \left(P_{pv-ev_i} - P_{grid-ev_i}\right) \tag{5}$$

where P_{pv-ev} is the power imported from the pv to the ev and $P_{grid-ev}$ is the power imported from the grid to the ev.

In general, the ev charging volume is not a straightforward process and can be influenced by many factors such as the condition and type of the vehicle, weather, the battery's SOC, daily driving patterns and the distance to the next destination. Unfortunately, due to privacy issues, such crucial information about the vehicle is almost never available so either some assumptions must be made or some implicit techniques must be used for their estimation.

The constraints that we will use here are:

$$P_{pv-ev_i} \leq \left(P_{pv_i} - P_{load_i}\right) \tag{6}$$

where it is expected that we must have a peak in the power imported from the pv, (P_{pv}) in respect to the power consumed to the other loads (P_{load}) in order to have a positive P_{pv-ev}. In addition, restrictions apply concerning the max and min capacity of the ev battery and also we want to make sure that there is enough energy for the ev's next planned trip:

$$P_{input} \leq P_{soc-max} - P_{ev-capacity-start} \tag{7}$$

$$P_{input} \geq P_{soc-min} + P_{next-trip} - P_{ev-capacity-start} \tag{8}$$

where P_{input} is the total load towards the ev coming from the PV and grid, $P_{capacity-start}$ is the EV's SOC at the beginning of the charging event and $P_{next-trip}$ is the power needed for the next planned trip.

The solver expects as input the timeseries data for energy production and consumption as well as the static specifications of the EV battery and the expected energy required for the next trip. As far as the latter parameter is concerned, it can be inferred using ML techniques such as clustering of the charging events, and finding daily trip patterns.

Other useful scenarios take into account other flexible loads in the dwelling, such as the HVAC and/or DHW. These scenarios are similar to the latter one, where the coupling of PV production with HVAC and/or DHW consumption is achieved through the solver. Their objective functions and constraints are out of the scope of this first version of the deliverable and will be identified in a later version.

3.2.4 Relationship with other frESCO modules

The **Energy Management Analytics Module** and the **Self-Consumption Optimization Module** (that reside in the GDM component) take input from the **Big Data Management Platform**, where all the available sensor, market and user data are stored. The **Energy Management Analytics Module** (GDM) receives user/device energy consumption usage information derived from the Personalised Energy Analytics Module and stored in the **Big Data Management Platform.** It appropriately aggregates information and feeds the **Self-Consumption Optimisation Module** which is responsible for delivering optimal notifications/control strategies back to the consumers as signals, always via the **Big Data Management Platform.**

3.3 Energy Analytics and Self-Consumption visualisation mockups

The Global Demand Manager (GDM) is the platform element closest to business users such as Aggregators and ESCOs. For the energy management analytics and the self-consumption optimisation, the communication with the ESCO is facilitated through a Graphical User Interface (GUI), with the ability for the user to:

- Produce reports with aggregated analytics.
- Interact with visualisations by selecting from dropdown menus.

Some examples from the visualisation mockups are presented below: Initially, when the user gets successfully authenticated and manages to login, he is directed immediately to the "at a glance page". In this page there is a summary of the most important aggregated KPIs relevant to the ESCO, at building level e.g. Building #16 of Krk Island demo.

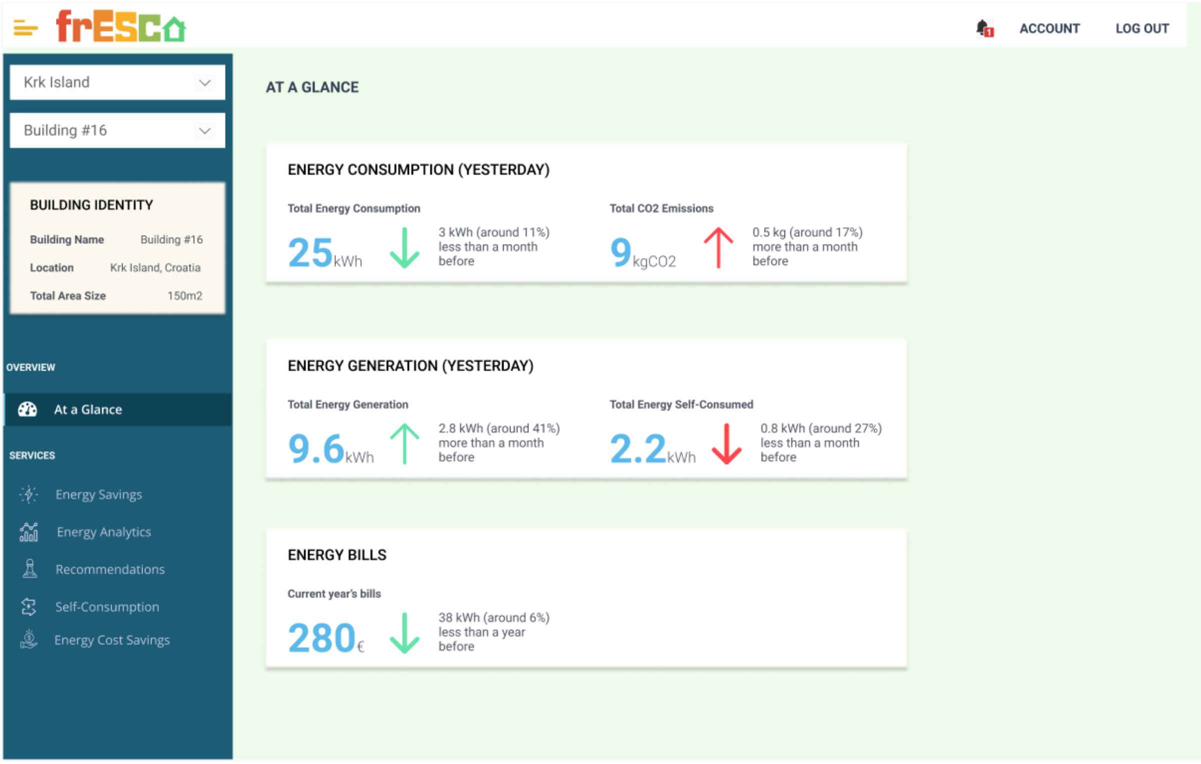


Figure 5. At a Glance page

The most interesting things relevant to the potential strategies that an ESCO can design and improve, are included in the "Energy Analytics page". Features like generation, consumption can categorise the prosumers into specific clusters (e.g. low, mid and high energy generation/consumption clusters) either at a building level or at a whole portfolio level. Seasonality patterns are also of high interest.

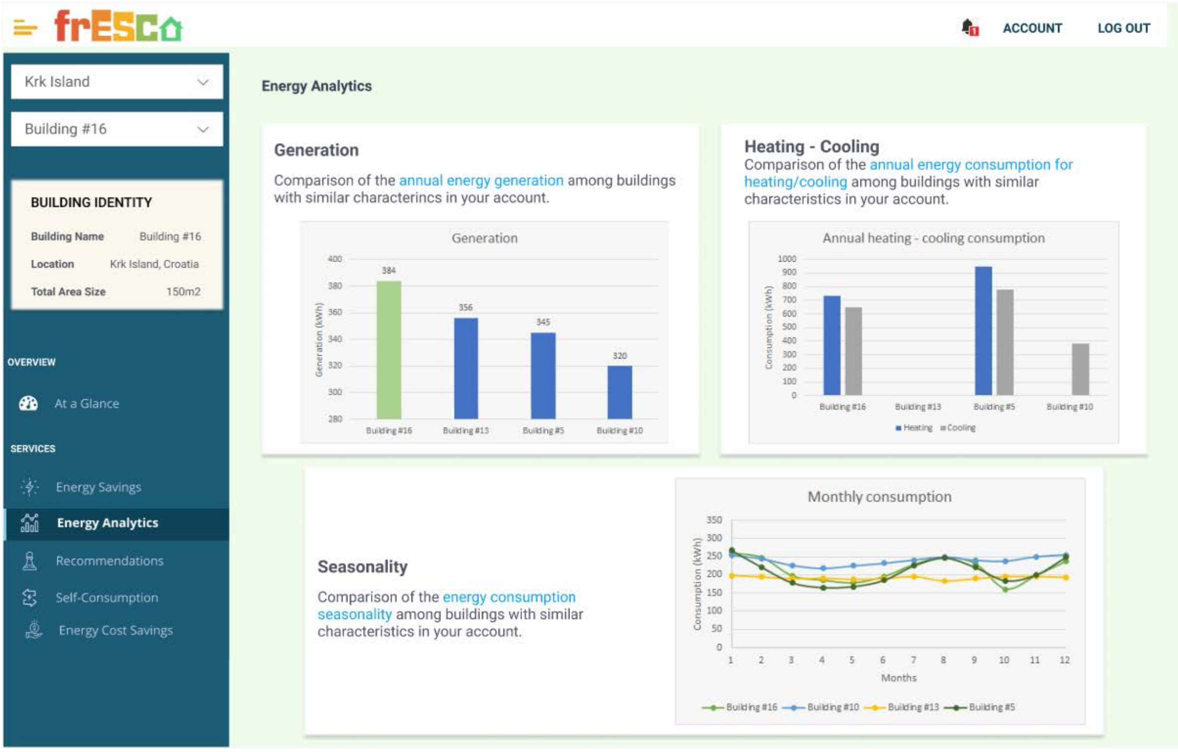


Figure 6. Energy Analytics Page

The "self-consumption page" shows the information on the past self-consumption rate at a daily and monthly level. There is the option for comparison with similar peers, which are actually other relevant buildings belonging to the ESCO's portfolio. Optimal time intervals are calculated, where the scheduling of flexible loads consumption is moved at times of peak generation. Let us note here that each demo may have its own self-consumption scenarios depending on the availability of the flexible loads, so the depicted information will be directly related to these specific assets.

Figure 7. Self-Consumption Page

Next we have the "Energy Savings page". The user can have an overall view of the savings regarding the total energy consumption as well as the heating/cooling savings at an annual and/or monthly level. Another relevant option is the "Energy Cost Savings page", where again cost savings due to the adoption of the self-consumption model are made available (monthly/yearly level).

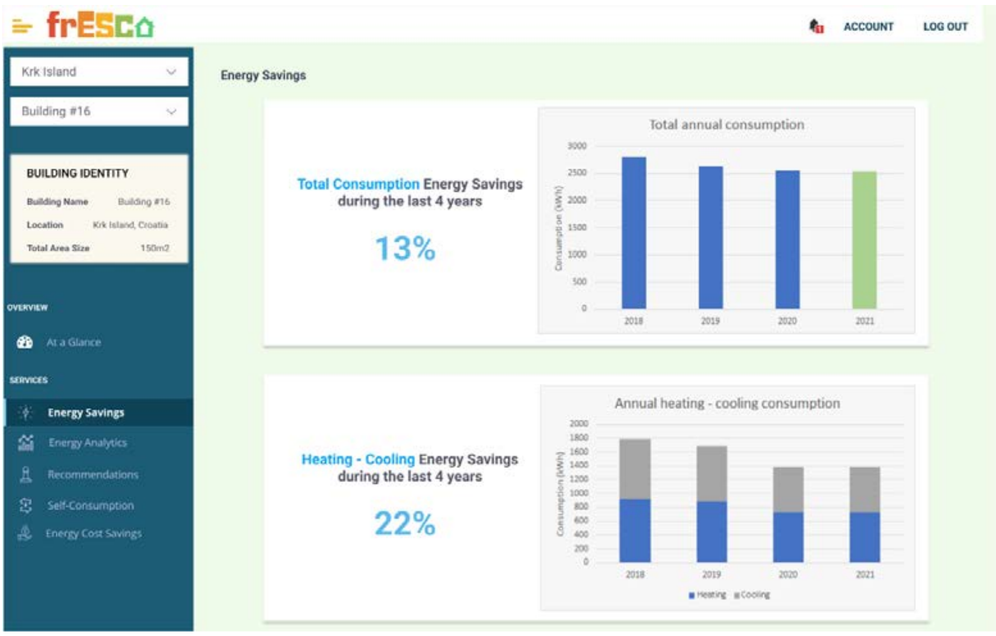


Figure 8. Energy Savings Page

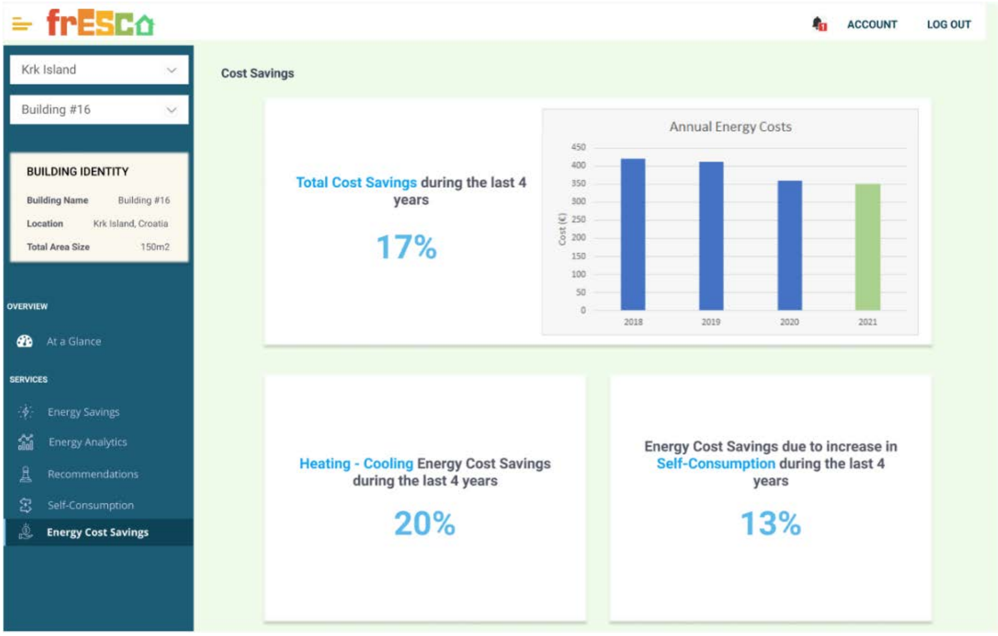


Figure 9. Energy Cost Savings Page

This is the first attempt to identify KPIs, diagrams and aggregated numbers that could interest the ESCOs and will be further refined through the course of the development of the frESCO project.

4 FLEXIBILITY ANALYTICS SERVICES AND VPP OPTIMISATION

4.1 Introduction and Requirements overview based on frESCO Use Cases

Explicit Demand response programs aim to reduce the electricity consumption of the end-users by making them active participants in the exchange of flexibility. Users are informed for a flexibility event (coming from the grid to the Aggregator) and according to their available flexible assets they can participate in the event either by switching off an energy intensive device, or by re-scheduling it to another timeframe of non-peak hours. The terms of that participation are defined in a smart flexibility contract between the aggregator and the user.

For the effective execution of these programs, a high level of automation and intelligence is required so that the fresco system can make short-term predictions regarding the total available flexibility at a given time, and respond proactively in an upcoming DR event. Constraints arising from the flexibility smart contract terms that the Aggregator and the user have agreed upon and signed, are also taken into account. The specific requirements that we are going to address for the flexibility services are those of D2.5 and are presented in the following table:

Table 5. ***Requirements relevant to the flexibility services from the Aggregators point of interest and their relationship with the relevant WP and UC.***

Req_001	The system shall have access to DER management system data.	WP4, WP6	UC.01, UC.02
Req_002	The system shall have access to EMS data.	WP4, WP6	UC.01, UC.02
Req_003	The system shall provide the possibility for the ingestion of real-time data assets.	WP4, WP6	UC.01, UC.02
Req_004	The system should have access to weather data.	WP4	UC.01
Req_005	The system should have access to wholesale market data.	WP4	UC.01
Req_007	The system should provide the possibility to a user to upload data files (i.e. csv, json, xml, etc.) or schedule future data asset uploads.	WP4	UC.01
Req_013	The system shall provide near real time monitoring of energy demand, generation, and consumption at dwelling level.	WP5	UC.01, UC.02, UC.03, UC.04, UC.05
Req_019	The system shall allow the aggregators to optimise their DR strategies considering DR attributes and dynamic electricity prices.	WP5	UC.07, UC.08
Req_022	The system shall allow the schedule of future flexibility activations.	WP5	UC.08
Req_023	The system shall allow the update and optimisation of consumer flexibility clusters (dynamic VPPs) to balance user comfort and flexibility remuneration.	WP5	UC.08
Req_024	The system shall provide forecasts of energy consumption trends.	WP4, WP5	UC.03, UC.04
Req_025	The system shall provide forecasts of energy demands and generations (mid-term and long-term) at dwelling level.	WP5	UC.05
Req_026	The system shall provide the possibility for short-term (day-ahead) energy demand forecast.	WP4	UC.05
Req_027	The system shall provide short-term weather forecast.	WP4	UC.04
Req_029	The system should allow configuration of flexibility assets into virtual power plants based on assets flexibility availability.	WP5	UC.08
Req_046	The system shall provide visualisation of information at different levels: individual, clusters, portfolio through a user interface for the aggregators.	WP5	UC.04, UC.05, UC.07
Req_049	The system shall provide information to the aggregator on ongoing/completed DR campaigns through a user interface.	WP5	UC.08

4.2 Flexibility and VPP configuration algorithms specifications

4.2.1 Input data and technology stack

The Flexibility Analytics Module and the VPP Optimal Configuration Module take input from the Big Data Management Platform, where all the available sensor, market and user data are stored. Moreover, for the simulation of Explicit Demand Response Events, the respective GUI will give the possibility to the aggregator to enter the details of the DR event (as described in the DR Event Data and Smart Contracts category). The parameters of the Smart Flexibility Contracts are acquired through the Smart Contract Monitoring/Handling Module always via the Big Data Platform. More specifically:

Sensor Data

- PV Energy Generation (kWh, time series)
- Building Energy Consumption (kWh, time series)
- Building Energy Storage (kWh, time series)
- External Ambient Temperature (ºC, time series)
- Indoor temperature (ºC, time series)
- HVAC Energy consumption (kWh, time series)
- DHW energy consumption (kWh, time series)
- EV energy consumption (kWh, time series)
- static properties of battery (battery_capacity , battery_charge_rate, battery_soc_max, battery_soc_min)
- static properties PV: nominal power, number of modules, modules datasheet
- static properties HVAC: nominal power output, efficiency
- static properties DHW: water tank volume capacity, nominal power output
- static properties of EV (ev_capacity, ev_charge_rate, ev_soc_max, ev_soc_min)

User Data

- Number and nominal characteristics of available flexible assets
- Weekly schedule
- Thermal, visual and air quality comfort profile

Market Data

- Flexibility electricity market bids and prices

DR Event Data and Smart Contracts

- DR_duration: The duration in minutes of the DR event
- DR_notice_period_length: The notice period in minutes before the actual signal of the DR event
- DR_reduction_request: The request made by the aggregator for a demand reduction in kW
- DR_penalty: The penalty for the aggregator if he fails to provide the requested demand reduction in euros
- Contract duration in years.
- Contract flexibility capacity in kW
- Contract number of activations
- Contract remunerations/penalties in euros

The Flexibility Analytics Module and the VPP Optimal Configuration Module are going to be delivered as a web-based application with the following tech stack:

- Backend: Django framework
- Frontend: Angular framework
- Databases: Postgres, Elasticsearch
- Analytics: Python and respective libraries like Pandas, Sklearn
- Deployment: Kubernetes

4.2.2 Algorithms for flexibility analytics for Aggregators

The extraction of demand flexibility profiles from domestic users as well as their flexibility registry nominal characteristics, as calculated in T4.4 will be used in order to assess the amount of available positive or negative demand flexibility based on very short (around 15 minutes) time forecasts.

Positive flexibility means the capacity to increase energy generation or reduce usage, while negative flexibility refers to decreasing energy generation or increasing usage. Either way, the grade of flexibility of a DER system depends on how quickly it can adapt generation or usage in response to external forces. This knowledge is very useful for the flexibility service providers such as Aggregators or Retailers, as they are in charge to prepare and offer smart flexibility contracts to their prosumers, negotiate their rules and thus attract customers from their portfolio into participating in DR programs. Customer segmentation is a very powerful tool to find patterns that will help the flexibility service providers to improve their DR strategies into more targeted and personalised campaigns.

Here as a customer segmentation tool, we implement a clustering engine based on Kmeans and DBSCAN. The reason behind choosing also a second clustering method is that Kmeans in order to work well, the following assumptions need to be true:

- the variance of the distribution of each attribute (feature) is spherical
- all variables have the same variance
- the prior probability for all k clusters are the same, i.e. each cluster has roughly equal number of observations

By features in this case we mean user energy consumption, demographics, contract criteria, types of flexibility assets etc. So in case the clustering of some of the aforementioned features produces unevenly sized clusters like for example if the aggregator's portfolio has a large cluster of residential consumers and a small cluster of commercial ones, the DBSCAN method is preferred. As other advantages, DBSCAN does not require a-priori specification of the number of clusters, and it is able to identify noise in data.

The produced clusters of prosumers/consumers provide the aggregator with useful insights, so in case of a new DR event they can identify targeted clusters that can act as Virtual Power Plants, to respond promptly in this DR event (we will analyse that aspect in section 4.2.3).

Moreover, some aggregated time series analytics will also be calculated here either at a cluster level or at a whole portfolio level. Examples are:

- average energy consumption per day/week/month
- average energy generation per day/week/month
- average energy storage per day/week/month
- average total available flexibility per 15/30 minutes

4.2.3 Algorithms for VPP optimisation for Aggregators

The optimisation process that we are going to follow is the standard methodology as described in the PuLP Python library, which we will use for solving our Linear Programming Problem (LPP):

- Define the problem
- Collect data and develop a Python model
- Solve with PuLP
- Validate solution: accept solution and go to implementation or decline solution and modify model

The definition of the problem can be further broken down into 4 key steps:

- Identification of the Decision Variables: Unknown quantities that represent the output of the LPP solution
- Formulation of the Objective Function: Maximisation or minimisation function that aims to evaluate the factor by which each decision variable would contribute to a value representing cost, profit etc.
- Formulation of the Constraints: Equations that describe the restrictions or limitations on the decision variables
- Identification of data needed for the Objective Function and Constraints

The VPP Optimal Configuration Module in the Global Demand Manager is responsible for maximising the potential of total available flexibility at a given timeslot, given a specific DR request from the grid.

In our case, every asset that is evaluated as flexible at a given time, participates as a decision variable in our VPP optimisation problem. So in case of DHW, HVAC, battery and EV flexible assets we get:

Decision Variables are the 4 available loads: P_{DHW}, P_{HVAC}, $P_{battery}$, P_{EV}

Objective function is the total available flexibility: $P_{DHW} + P_{HVAC} + P_{battery} + P_{EV}$

Constraints:

$$P(t)demand \leq \sum_{i=1}^{N} P_i(t) \leq P(t)contracted \tag{9}$$

where $P(t)_{demand}$ is the requested amount of flexibility in kW at a given time step, N is the total number of available flexible assets, $P_i(t)$ is the load of each flexible asset at a given time and $P(t)_{contracted}$ is the maximum contracted power as agreed in the corresponding smart contract between the prosumer and the aggregator. With regards to the general electricity balance, and having in mind that the major assets under consideration here are PV, EV, Battery, HVAC and Domestic Hot Water (DHW) the sum of electrical generation and consumption must be equal:

$$P^{PV}(t) + P^{Grid,in}(t) + P^{BAT,disch}(t) = P^{DHW}(t) + P^{HVAC}(t) + P^{EV}(t) + P^{BAT,ch}(t) + P^{Grid,out}(t) + P^{Load}(t) \quad (10)$$

where P^{PV} is the power generation, $P^{Grid,in}$ and $P^{Grid,out}$ are the power import and export with the grid, $P^{BAT,disch}$ and $P^{BAT,ch}$ are the discharging and charging power of the battery, P^{DHW}, P^{HVAC} , P^{EV} is the electrical power consumed by the DHW, HVAC and EV respectively and P^{Load} represents any other non-flexible load in the dwelling.

As we proceed in the implementation of the VPP optimisation, more constraints will be identified (based for instance, on the HVAC nominal power output, HVAC efficiency, DHW tank volume capacity, DHW nominal power output), and so the optimisation problem will be further enhanced in the second version of this deliverable, D5.2. Another example is the addition of the user thermal comfort in the constraints, as the optimisation cannot compromise the min, max thermal comfort boundaries.

4.2.4 Relationship with other frESCO modules

The **Flexibility Analytics Module** and the **VPP Optimal Configuration Module** (that reside in the GDM component) take input from the **Big Data Management Platform**, where all the available sensor, market and user data are stored. The **Flexibility Analytics Module** (GDM) receives the smart contract parameters/criteria from the **Smart Contract Monitoring/Handling Module** (GDM) and sends the flexibility signals to the **Human Centric Automation Module** (that resides in the LDM component) for the realisation of the control actions on each user's assets, always via the **Big Data Management Platform.**

4.3 Flexibility and VPP visualisation mockups

The Global Demand Manager (GDM) is the platform element closest to business users such as Aggregators and ESCOs. For the flexibility analytics and the VPP optimisation, the communication with the Aggregators is facilitated through a Graphical User Interface (GUI), with the ability for the user to:

- Insert new DR events and their characteristics.
- Produce reports with aggregated analytics.
- Interact with visualisations by selecting from dropdown menus.

Some examples from the visualisation mockups are presented below: Initially, when the user gets successfully authenticated and manages to login, he is directed immediately to the "at a glance page". In this page, there is a summary of the most important aggregated KPIs relevant to the Aggregator, at demo level e.g. Krk Island demo. Possible KPIs are (but are not limited to): number of current consumers, number of total flexibility assets, the average number of daily DR events, the average amount of flexibility delivered daily etc.

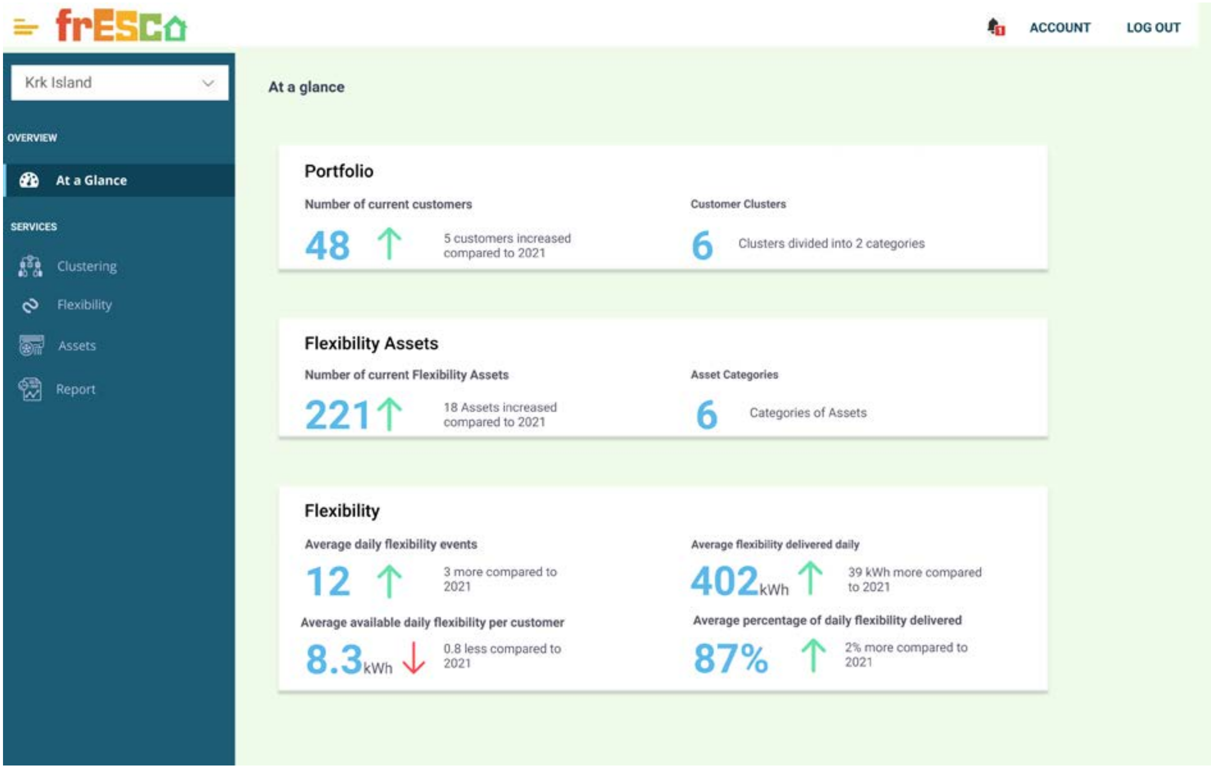


Figure 10. At a glance page

"Clustering page" at user and asset level, can provide valuable information on the design of the tailor-made flexibility strategies that will be stored in the Big Data Management Platform and delivered in each identified cluster of consumers upon each simulated flexibility request from the grid.

Figure 11. Clustering page

The "flexibility page" helps the Aggregator to construct the simulated DR events, since we are not having a grid operator as a stakeholder in the frESCO project, and have an overall look at the flexibility requested, flexibility provided, short-term prediction on the available flexibility (e.g. 15 minutes ahead) etc.

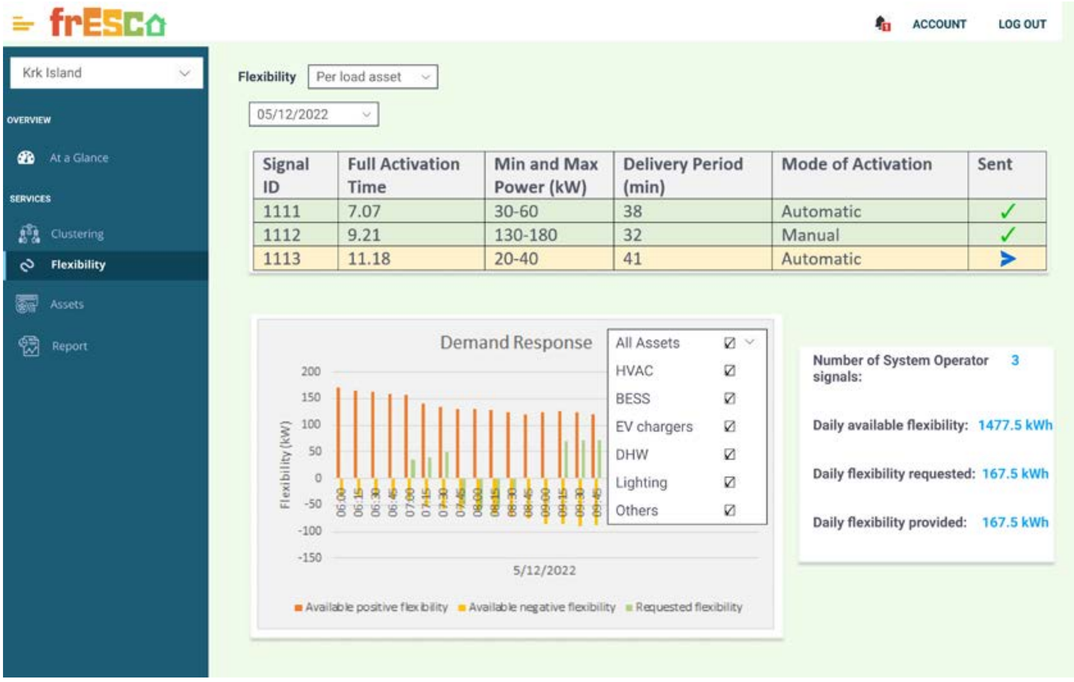
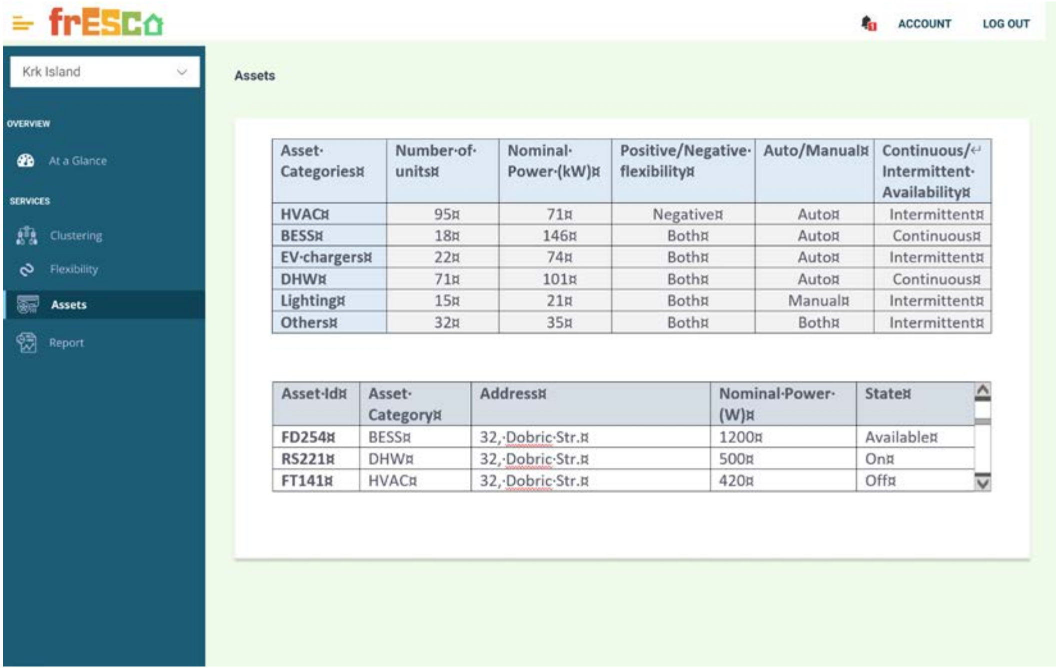


Figure 12. Flexibility page

The "Assets page" gives aggregated information on the flexible asset categories, average nominal power, type of flexibility, operating mode, state etc. And finally the "Report page" gives the possibility of exporting a pdf with a small summary at monthly level of positive/negative flexibility per asset category as well as the average hourly flexibility delivered on a specific day that the user will choose to acquire the report on.



Asset Categories	Number of units	Nominal Power (kW)	Positive/Negative flexibility	Auto/Manual	Continuous/Intermittent Availability
HVAC	95	71	Negative	Auto	Intermittent
BESS	18	146	Both	Auto	Continuous
EV chargers	22	74	Both	Auto	Intermittent
DHW	71	101	Both	Auto	Continuous
Lighting	15	21	Both	Manual	Intermittent
Others	32	35	Both	Both	Intermittent

Asset Id	Asset Category	Address	Nominal Power (W)	State
FD254	BESS	32, Dobric Str.	1200	Available
RS221	DHW	32, Dobric Str.	500	On
FT141	HVAC	32, Dobric Str.	420	Off

Figure 13. Assets Page

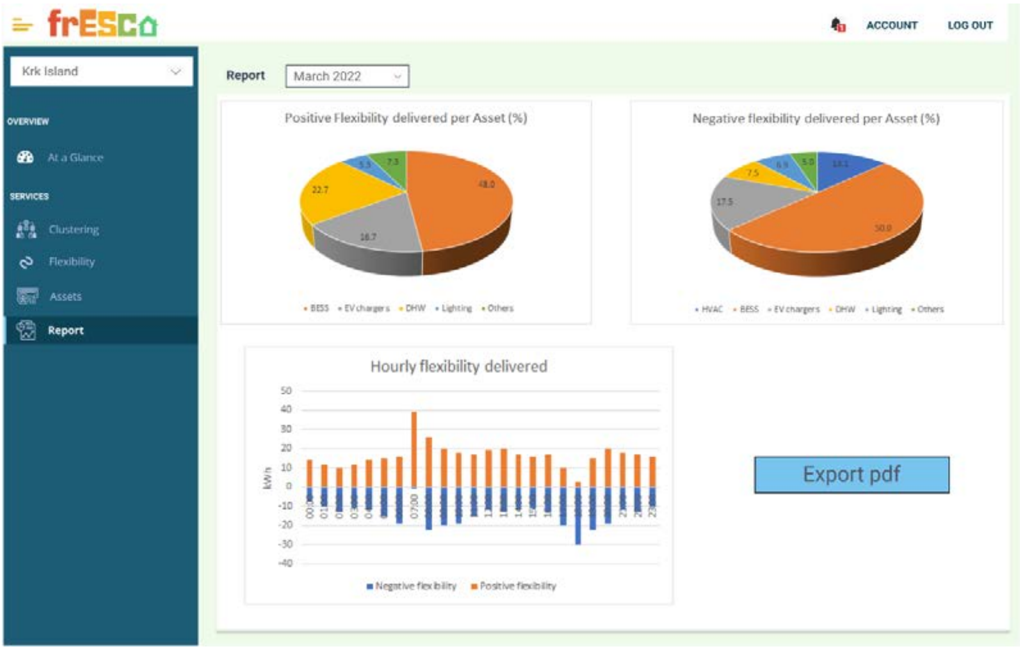


Figure 14. Report page

This is the first attempt to identify KPIs, diagrams and aggregated numbers that could interest the Aggregators and will be further refined through the course of the development of the frESCO project.

5 CONCLUSION

To summarize, this deliverable, covering tasks 5.1, 5.2 and 5.3, has presented several methodologies around the development of energy efficiency and flexibility services and the visualization of descriptive and predictive analytics for various stakeholders such as prosumers, ESCOs and Aggregators. Applications presented ranging from simple monitoring of aggregated sensor measurements, clustering of the prosumers according to various features, time series analysis of trends and patterns in demand and generation, and optimisation algorithms regarding self-consumption and flexibility have been presented and analysed.

The delivery of analytics insights to the end-user is of crucial importance, that is why dedicated mock-ups have been designed and implemented regarding the passive delivery of information as well as the proper user interaction possibilities, according to the relevant stakeholder consumer/prosumer, ESCO, Aggregator.

The added value of this deliverable is that its results can be used in conjunction with the results from WP3, Novel Performance-based Business Models and Verification Method for bundled energy services, towards the design, development and deployment of new business P4P services, generating even more significant benefits for all parties involved.

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