ACCELERATING THE DECARBONIZATION OF ISLANDS' ENERGY SYSTEMS

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DELIVERABLE 1.3:

OPTIMAL DESIGN OF THE ENERGY GRID

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TABLE OF CONTENT

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ABBREVIATIONS

CPU: Central Processing Unit
DER: Distributed Energy Resources
DR: Demand Response
EV: Electric Vehicles
HES: Hybrid Energy Storage
IEC: International Electrotechnical Commission
LP: Linear Programming
MILP: Mixed Integer Linear Programming
O&M: Operations and Maintenance
POA: Plane of Array
PV: Photovoltaic
SOC: State of Charge
STC: Standard Test Conditions

EXECUTIVE SUMMARY

Description:

This task will pose and solve the mathematical optimisation problem previously described in section 1.2.

The objective is to obtain the optimal set of design parameter for every DER and HES system, and grid couplings, to be deployed in the island.

Methodology:

To achieve the goal of optimizing all the installations on the island, a mixed integer linear programming model has been developed.

It is a modular problem, composed of different modules which can be activated or deactivated at will. Each module is a component of the island's energy hub.

Once created, the model is given to a solver, which finds the optimal solution to the problem: the optimal installations sizing which will minimise costs.

Work plan:

- Starting from the specific independent models defined in D1.2 (Ayesa Advanced Technologies, 2021), outline a first version of the global optimization model
- If necessary, modify the modules adding new features and possibly define new modules
- Select the solver and integrate it with the model
- Collect all the necessary data and parameters from Borkum (and follower islands), to

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run the model for the specific case

- Get the results and analyze them, possibly tuning parameters and trying different configurations.

Blocking points:

The complexity of the model has been one major blocking point for the task. Initially the development of the different modules has been too detailed, with the intent of simulate the most adherent to reality energetic behavior.

The blocking point was overcome by identifying the cause of the computational time increase and simplify the model in the most effective way. Also, the usage of a commercial solver has been adopted to enhance performances.

Conclusions:

The results given by the model are consistent and lend themselves to interesting analysis. Unfortunately, they do not refine the initial installations set in the grant agreement, they rather paint an ideal scenario in which the island of Borkum is completely decarbonized and autonomous.

In the optimal design all passible DER & HES are selected by the solver, pointing out that a mix of different technologies is the best choice.

1 INTRODUCTION

ISLANDER has as an overall objective to **implement several innovative actions in the field of Energy to decarbonize islands**. The demonstrator will be the Island of Borkum in Germany, but the replicability will be under the scope of the project including other European Islands in Greece, Croatia, and UK.

In relation to this deliverable, ISLANDER aims to develop an **optimization framework**, to design the future combination of energy assets to decarbonize geographical islands. This optimization framework will have a general approach, that will be validated with the use case of the Borkum island. To that end, it is necessary to mathematically model all the energy related assets. **Deliverable D1.2** (Ayesa Advanced Technologies, 2021) was dedicated to present the modelling approach and this deliverable is devoted to defining the general model and presenting the tool that allows to solve it, with the flexibility to adapt to a specific scenario, such as Borkum's or the one of any other follower islands.

In the next section, **DEFINITION OF THE SIZING PROBLEM**, the concepts from previous Deliverable D1.2 (Ayesa Advanced Technologies, 2021) are elaborated and integrated with new information. The goal is to describe the general island's situation and the type of installations planned, and to pose the premises for the mathematical model.

In the third section **OPTIMIZATION MODEL** the whole functioning of the program is described. First, a small introduction to MILP (Mixed Integer Linear Programming) clarifies what type of model was used and what are the main components. Then the specific structure of the ISLANDER optimization model is introduced, explaining the **modular nature** of the model, and its flexibility. Finally, every single module is described, with all its parameters, variables, restrictions, and contribution to the objective function.

The section **OPTIMIZATION APPROACH** is dedicated to the presentation of the problems

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posed by the development of a model of this nature, and of how they were overcome. There is also a subsection dedicated to the choice of the solver used in the optimization, and the hardware specifics.

The final section OPTIMIZATION PERFORMANCE: RESULTS presents the results of the model, launched with Borkum's parameters. Different scenarios with different modules are evaluated and the results of each run leads to some interesting considerations, recollected and summarized in the MAIN CONCLUSIONS chapter.

2 DEFINITION OF THE SIZING PROBLEM

The ISLANDER project aims to provide an island with the necessary infrastructure to meet its energy needs through renewable technologies. This objective must take into consideration that the sizing of the technology implemented to decarbonize the island must be optimized by minimizing a fundamental parameter such as the cost of the project. To address this problem, it is first necessary to keep in mind the types of technologies that can be implemented on the island under study, as well as their characteristics.

Currently, the island of Borkum has the capacity to supply the energy demand of its inhabitants through conventional sources of energy through fuels, solar energy sources (thanks to the generation from photovoltaic panels), wind energy (through windmills that will soon be dismantled), and through an interconnection system that the island has with the mainland. The initial approach that has been developed to supply the energy demand with renewable sources includes the following aspects:

- Increasing solar energy capacity by installing photovoltaic panels both in homes and in factories or buildings. This type of users will be able to be both energy producers and consumers, which is why they have been defined as *prosumers*.
- The installation of new windmills using both off-shore and on-shore technology.
- The creation of new energy storage facilities to be able to use it at the most appropriate time. For this purpose, Li-ion technologies and a hydrogen storage system have been chosen.
- To develop a combustion-free mobility system by creating charging points for electric vehicles.
- The usage of the interconnection cable with the mainland if necessary.

Figure 1 shows the interconnection model of Borkum Island.

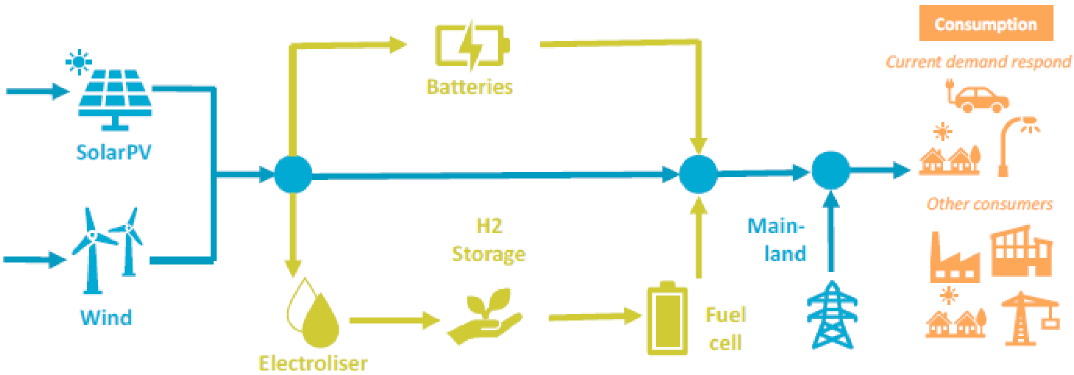

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Figure 1. Interconnected model of Energy grid. Source: Deliverable D1.2 (Ayesa Advanced Technologies, 2021)

To determine the sizing of all this infrastructure, and at the same time minimize the necessary cost, a mathematical model has been developed to optimize the installation size by minimizing an objective function based on the cost associated with each technology.

2.1 Importance

The optimisation model is a simplified representation of an island's energy hub. The solutions are the optimal installation sizes of the assets to minimise costs by meeting all the criteria (restrictions). It is an innovative work and represents an important step of the project, providing a tool able to study different cases and scenarios. However, as mentioned above, the model approximates the real situation of the island, and therefore the results should also be taken as an approximation. The sizing values given by the model provide a baseline to work with and should be taken into account among other considerations.

The versatility of the model comes from its modular nature: there are 10 different modules which can be switched on or off depending on the needs of the island. Each module reaches a high level of detail, usually requiring a broad set of parameters.

Ideally the final user should be able to provide all the necessary parameters to activate the modules they are interested in, and make different tests by tuning some of the parameters, or activating different modules.

2.2 Preliminary design

The Gran Agreement document establishes the predominant climate in Borkum, which is characterized by high winds in winter and mild summers. Even though the environmental conditions normally vary greatly during the day, a proposal has been made to install several renewable energy systems to take full advantage of the climatic characteristics that define Borkum. Figure 2 contains a summarize of all of them.

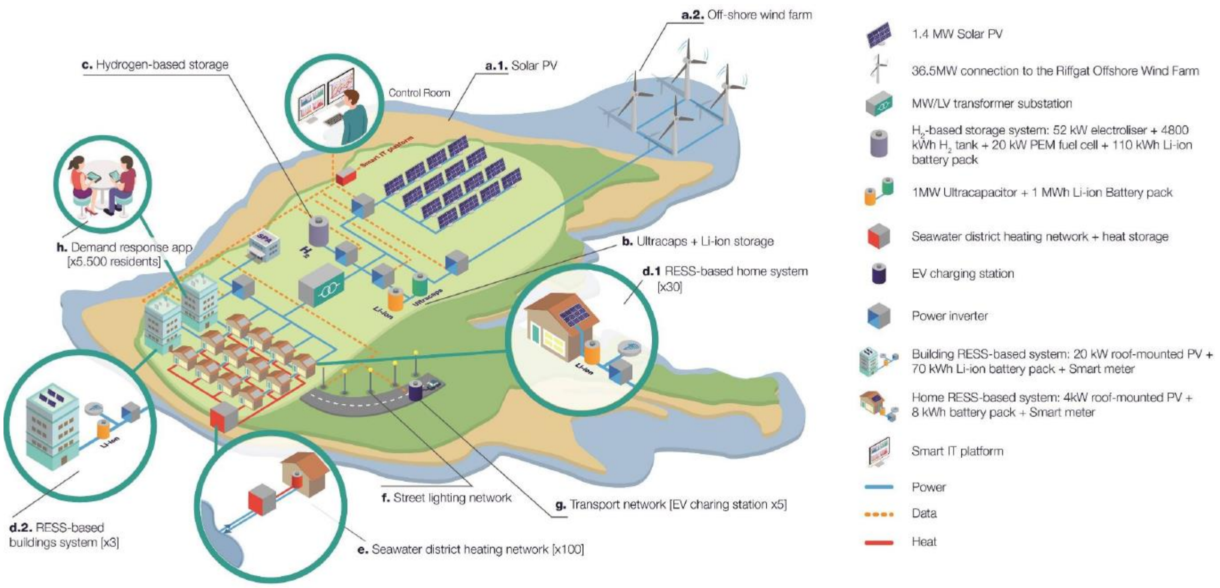

Figure 2. The ISLANDER concept for making Borkum a fully decarbonized and smart island. Source: Grant agreement.

A brief additional information for all the previous renewable systems, included in Grant

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Agreement, is given as following:

- Renewable power plants. This group includes a 1.4 MW solar photovoltaic plant and several wind turbines with a total capacity of 36.5 MW. These infrastructures are present in the model, although the wind turbines will have to be dismantled due to geographical issues.
- Grid-level storage. Consists of a 0,45MW ultracaps systems, composed of a series of high-capacity capacitors, and a Li-ion battery pack of 0,61MWh, which benefits from the combination with the ultracaps system. Ultracaps are not included in the model, since the advantages of such installation can be appreciated on small-scale timeseries (of the order of seconds). The model on the other hand optimises the installations on a full-year scale simulation, with granularity of one hour (at most).
- Hydrogen-based seasonal storage. To provide flexibility to the smart IT platform, the following elements have been incorporated: a 52 KW electrolyzer, a pressurized hydrogen tank with a capacity of 4,800 kWh for long-term storage, a 20kW fuel cell to provide electricity as well as residual heat for the island's district heating network, and finally, a Li-ion battery pack of 110 kWh to stabilize system voltage levels.
- Distributed household/building RESS solutions. Regarding to household, the system is composed of 4 kW roof-mounted PV, an 8 kWh Li-ion battery storage. On the other hand, each building RESS solution will be composed of 80 m2 PV roof installations delivering 20 kW, a Li-ion battery set with storage capacity of 70 kWh.
- District heating network. The NBG partner expects to develop a district heating network pilot in the Reede area for 100 residential units using the concept of "heating with the North Sea". This technology is not included in the optimisation model, which focuses only on the electric grid.
- Street lighting network. The system consists of 1,100 light points. It is independent from the grid and has a hybrid system of a 4kW photovoltaic installation, a 15 kWh lithium battery group, an inverter and a smart meter.
- EV transport network. Borkum currently has a fleet of 14 electric vehicles (including two buses) and a total of 3 charging stations. ISLANDER intends to increase the infrastructure with 5 additional charging points.

Previously, in deliverable D1.2 (Ayesa Advanced Technologies, 2021) a series of diagrams were included showing the criteria adopted to determine the energy balance of each of the interconnection models shown in Figure 2. Each of the interconnection models depends on a series of input parameters to define its behaviour model such as: meteorological data with annual time periods, consumption patterns, design parameters of the asset etc. These initial models were used as a starting point for the optimal design of the energy grid that characterizes the island. However, they were not enough to optimize all the installation sizes since they were independent from one another. Therefore, the mathematical model to be presented below requires that each of the models is reformulated to be linear with respect to the sizing variable, so that the minimum of the objective function can be found. In the following section, this deliverable will focus on defining the general model, made of each of the linear modules introduced in D1.2 (Ayesa Advanced Technologies, 2021).

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3 OPTIMIZATION MODEL

3.1 Modelling strategy

There are several different approaches to mathematical optimisation, and within every approach, many different techniques and models. Probably the most classical approach is the one taken in the Operational Research branch of mathematics. Among this branch the most common type of problems are the linear ones, which are usually solved using Linear Programming (LP).

A LP problem consists of:

- Variables: these are the elements to be optimised, are defined in the space of real numbers, and finding their optimal value defines a solution to the problem. The variables define a space, it is a vectorial space of dimension the number of the variables (i.e. each variable adds a dimension).
- Restrictions: they are generally in the form of inequalities. The restrictions define the domain (inside of the space of the variables) in which the variables can *move*. Any set of values outside of the domain defined by the restriction is not considered a feasible solution.
- Objective function: it is a mathematical function that depends on (some of) the variables of the problem. It can be minimised or maximised and represents the goal of the optimisation: for instance, trying to minimise some working time, it could be the sum of all the time dedicated to each task.

In a LP problem all the restrictions and the objective function *must be linear* with respect to the variables. There is a good number of parameters defining the problem. These parameters can be obtained in any different nonlinear way, since in the end they are nothing but numbers to multiply the variables.

The variables on the other hand, can only be multiplied (or divided) by parameters, and then summed up. There is no other possible operation that can be done with variables in linear programming.

Once all the elements are defined, the goal of the optimisation is to find the set of (feasible) values for variables, which returns the minimum (or maximum) possible value when substituted in the objective function.

If one or more variables are only allowed to take *integer* values, the solving methods change, and they are part of Mixed Integer Linear Programming (MILP). In this case finding the solution is generally more complicated the more integer variables are added to the problem. The model presented in this document, in general, is a MILP problem.

Currently LP and MILP models are solved using specific software that can handle a variety of different cases and type of problems. In this document this kind of software will be called *solvers* from this point onward.

We chose to write the model in python, using the library *pyomo* (pyomo, 2022), which offers great flexibility in the way problems are written, and works with a huge number of different solvers. Free solvers have often decent performances, especially if the right one is chosen depending on the type of problem. They make a good testing tool and are often able to solve medium size problems (the size of a problem refers to its number and type of variables), making a good baseline for performances. With a big sized problem like this one however, they did not suffice the purpose, and that is why CPLEX from IBM was used. It is a commercial solver able to handle LP, MILP and other type of problems, with a much better performance of the average free solver available (Templ, 2012).

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The flexibility of pyomo, however, makes it very easy to anyone using this same program to utilize the best solver they see fit or have available, given it is compatible with pyomo.

It also allowed us to develop the program in a **modular architecture**, meaning it is not only a problem with tuneable parameters, but an entire compartment (module) of the model can be activated or deactivated at will. The modules of the model are:

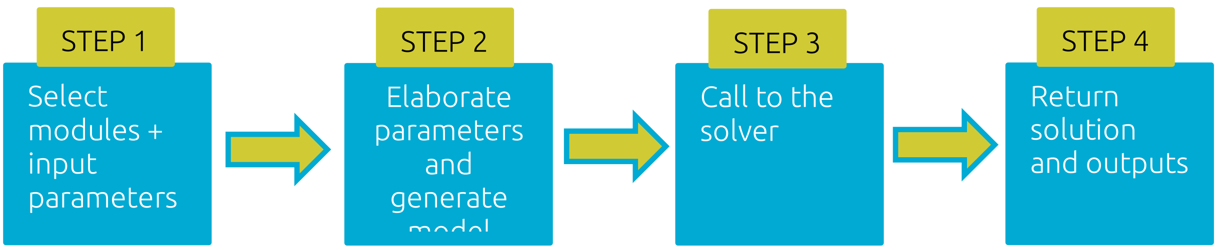
- Solar generation
- Wind onshore generation
- Wind offshore floating generation
- Wind offshore founded generation
- Battery storage system
- Hydrogen-based storage system
- Prosumers (solar gen. + batteries)
- Existing interconnection
- New interconnection
- EV charging points

Through a configuration file, the end user must specify some general parameters of the model (including the solver they will be using), and then which of the modules they want to be activated in the phase of creation of the model. For every module they will activate, they will also have to specify all the module's parameters, described in the following sections.

In the future this configuration process of input parameters will be available through an interface in the Ayesa SmartIT platform.

Each module will add its own variables, constraints, and contribution to the objective function to the model, as described in the following section.

This flexibility and modularity of the program affects only the part of creation of the model, which comes before the call to the solver. Every time a module is activated/deactivated, or a single parameter is changed, the whole program must be run again, and hence the problem that is being created (and then solved) is a different problem from the one of the previous run.



After the solution is found, all the values of the sizing variables are saved in a file, alongside all the operational variables (not all variables are sizing variables, as explained in the following sections), and some plots of the most significant values are generated, to understand the behaviour of all the systems and the reasons behind the optimal sizing found by the solver.

3.2 Objective function

The objective function of the model is a **cost function**. Cost objective functions are very typical of LP optimisation, used in many problems in which expenses are being minimised, including energy hubs models (Martin Geidl, 2007) (Alejandro J. del Real, 2008). The costs are parameters the end user needs to provide and are divided between installation costs and

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Operation and maintenance (O&M) costs. The installation costs multiply the sizing variables, whereas the O&M costs multiply the sum of all the energy either generated or flowing through the module.

Its structure is the following:

$$\sum_{modules} c_{inst} \cdot P + \sum_{modules} (c_{O\&M} \cdot \sum_{t=1}^{T} E(t))$$

Where P is the sizing variable of each installation (generally a power value [kW]) and $E(t)$ is the energy flowing through (or generated by) the installation at time t.

3.3 General structure

In order to optimise the sizing of the installations, the model simulates the behaviour of the electric grid of the island over a period of time. For this purpose, different timeseries of data are needed, such as the consumption timeseries and weather condition timeseries. Specifically, the weather conditions are wind speed, irradiance and, possibly, temperature on the panels.

The optimisation is better performed on a long period of time, ideally one year, so that all seasons' weather conditions are included, and the seasonal usage of some of the installations (e.g. hydrogen storage system) can be developed. It is for this reason that historical timeseries must be used in the optimisation. Specifically, the yearly consumption of 2019 was used, because of behavioural changes related to the Covid-19 pandemic of 2020.

The granularity of the timeseries must be hourly, although that can be manipulated within the program. For instance, there is the option to group hours in order to reduce the total number of timesteps, if the complexity is too high. As explained in later chapters of the document, complexity and solving time is an issue for a model of this size, and changes depending on the number and type of activated modules, and the number of timesteps.

Let us call $t = 1, \dots, T$ the timesteps, where T is the total number of timesteps of the model (ideally $24 \times 365 = 8760$).

The first and most important constraint, as well as the only one that is affected by every single module in the program, is the **energy balance** constraint. Let $L(t), t = 1, \dots, T$ be the island's consumption timeseries. The energy balance constraint forces the consumption to be met at every timestep by the generation of the island. The general structure of the constraint would be:

$$L(t) = G(t) + S(t)$$

Where $G(t)$ sums up how much every generation source active on the island is generating at time t, whereas $S(t)$ is the sum of all energy flows through the storage systems.

This must be true at every timestep, meaning that this defines a total of T restrictions, and they are the core restrictions of the problem. All other restrictions are internal to the modules, and their purpose is to model the behaviour of the module itself.

Every activated module will contribute either to $G(t)$, to $S(t)$ or to both.

3.4 Individual modules

During D1.2 development (Ayesa Advanced Technologies, 2021), main engineering models were developed. Within this deliverable they will be modelled to be included in the linear model given to the solver.

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All these engineering modules are going to be divided into generation, storage, interconnection, prosumers, and mobility.

The aim of this section is to provide a clearer explanation of the structure and information of each of the modules included in the optimization model. To achieve this goal, each of the models mentioned above will contain information related to the following points:

- A **general overview** will offer a representation of the functioning of the module analysed.
- **Input parameters**. A brief explanation of the engineering concept is included to have a wider knowledge of the module. This point contains the inputs parameters that are specific for each asset. The end user should be able to provide all the parameters needed for the modules they want to activate, although some of the parameters have default values that can be used.
- **Variables** of the module. Every module has at least one sizing variable, representing the size of the installation and being the final goal of the optimisation. However not all the variables represent the size of an installation. Some variables, called *operational*, represent a quantity of energy at a determined timestep (e.g. the energy entering or exiting a battery at a certain time). These variables are far more numerous than the sizing one, since *one for each timestep* is needed.
- **Internal constraints**. Each module has its own space defined by several boundaries where the solver can find the optimal value of the objective function. Therefore, it is necessary to define the internal constraints associated with each of them.
- Contribution to the **energy balance**. The global energy consumption on the grid must met by the generation. So, it is necessary to define at each timestep how each module will contribute to the energy balance.
- Contribution to the **objective function**. Once previous steps have been completed, the optimization function can be minimized. This section will include how each module will contribute to the formulation of the objective function, or, in other words, the costs associated to each module.

3.4.1 Solar generation

First module to be analysed is related to PV technology, and it consists of a solar PV plant. Since household/building PV installation usually have different characteristics, they are considered in a separated module, called *prosumers*. This type of technology usually combines the use of PV modules to produce the energy, a set of batteries to store the residual electricity and inverter to convert the electricity provided by PV modules. In the model however, the battery module is separated from the PV one, hence it is only recommended, and not mandatory, that they are activated both at the same time.

Solar PV generation model

Solar photovoltaic model simulates the behaviour of a solar park .

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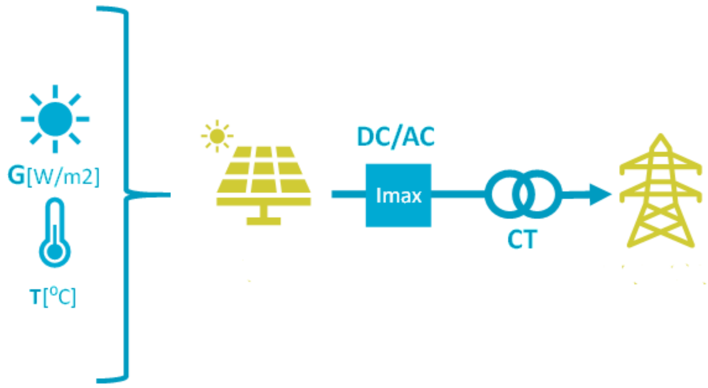

Figure 3. Representation of the solar PV island's installations.

The following is an explanation of the most important parts that make up the solar photovoltaic calculation module.

In the present deliverable an alternative method to obtain the output power of the photovoltaic panels is proposed. Unlike the method described in deliverable D1.2 (Ayesa Advanced Technologies, 2021), this procedure takes into account the standard conditions established by the manufacturer. In this way, an overview of the status of the PV system according to the international IEC 61724 standard can be obtained. In addition, parameters related to weather corrections and degradation parameters can be added to obtain a more accurate result.

$$P_{PV}(t) = P_0 \frac{H(t)}{G_{ref}}\left[1 + \gamma\left(T_m - T_{ref}\right)\right](1 - d)^n \quad \text{[Equation 1]}$$

Output PV modules can be affected by meteorological conditions. If a user prefers to eliminate the effects of both the ambient temperature and wind, the weather-corrected term can be applied following the expression $[1 + \gamma(T_c - T_c^*)]$.

On the other hand, degradation parameter can be added if datasheet from manufacturer is available. This term is calculated applying the last term of the [Equation 1], $(1 - d)^n$.

Input parameters

Design parameters

A brief description of all parameters contained on it are listed below:

- P_p denotes the peak power of a single panel [kW] (provided by the manufacturer)
- $H(t)$ determines the measured plane of array (POA) irradiance [W/m2]. It is a time-dependent input and needs to be given to the model as an array.
- G_{ref} established the irradiance at standard test conditions (STC) [1,000 W/m2].

Regarding the weather-corrected factor the terms used are the following:

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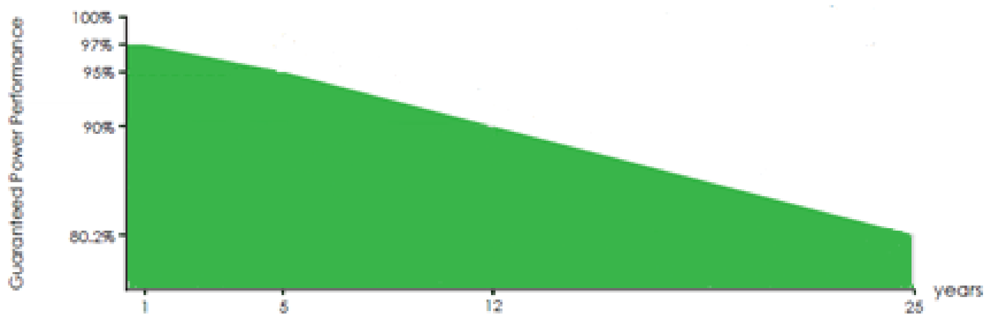
- T_m is the cell temperature from PV panel [°C]. In case the user does not have this parameter, it will not be factored in the generation equation.
- T_{ref} represents the temperature at standard test condition [°C].
- γ is temperature coefficient for power [%/°C, negative in sign] that corresponds to the installed modules.

And respect to the degradation factor, parameters d and n must be obtained through the datasheet from manufacturer as follow:

- $d = 1 - \sqrt[y]{\eta_y}$ represents de degradation over the years.
  - η_y is the final guaranteed power performance established by manufacturer. Following the next figure, it is equal to 0,802.
  - y is the final year established by manufacturer. Following the same picture, this parameter takes a value of 25.



- $n = \frac{c_d - c_c}{365}$, on the other hand, represents the period of the degradation.
  - c_d indicates the last day of the analysis
  - c_c is the commissioning day.

Available spaces

- $S_{tot,PV}$ is the total available space on the island though to install the solar PV park [m^2]
- $S_{kW,PV}$ is the space occupied by a single kW of installation [m^2/kW]

State of the current installation

- $Installed_{PV}$ Power installed previously on the island [kW]

Cost

- $C_{inst,PV}$ is the installation cost per peak kW [€/kW]
- $C_{O\&M,PV}$ is the operating and maintenance cost per kWh produced [€/kWh]

Variables of the solar PV module

The total number of total PV panels that need to be installed on the island will be the sum of the peak power associated with the PV plant plus the panels that need to be installed on the household and buildings. In later sections, the procedure for determining the number of PV panels needed to be installed on rooftops will be shown. In the meantime, this section will provide the necessary information for the sizing of the solar park.

Of the set of terms appearing in [Equation 1], the peak power P_0 is the only variable to be optimised. Its value will provide insight into the size of the PV plant that the island should contain. It is defined as a non-negative real value:

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$$P_0 \geq 0$$ [Equation 2]

The option of using the number of panels to be installed as an integer variable has been taken in consideration. However, integer variables increase the complexity of the model substantially, and hence the computational time. In this case an integer variable would not add relevant precision to the solution of the model, and the integer value can be computed afterwards using the parameter P_p.

Internal constrains

The interval of accepted values for P_0 is defined by the following constraint:

$$Installed_{PV} \leq P_0 \leq {S_{t,PV}}/{S_{kW,PV}}$$ [Equation 3]

To be able to adapt the model to the necessities of each island, spatial constraints are introduced. Specifically, if an installation of a module takes a certain amount of space, the total space taken cannot be greater than the space assigned to that module in the beginning.
Moreover, there is the option for every module of setting some initial installation that are already present on the island. Therefore, the sizing variable cannot be smaller than the sizing of the current installation.

Contribution to the energy balance

Being the solar park a generation module, its contribution to the energy balance is the amount of energy generated at each timestep.
It is defined as follow:

$$P_0 \cdot \frac{H(t)}{G_{ref}}\left[1 + \gamma\left(T_m - T_{ref}\right)\right](1-d)^n$$ [Equation 4]

Objective function

In case the module associated to the PV plant is active, the following expression will be added to the objective function of the model:

$$C_{inst,PV} \cdot P_0 + C_{O\&M,PV} \cdot \sum_t P_{PV}(t)$$ [Equation 5]

It is the sum of two parts: the installation cost of a panel multiplied by the number of panels and the O&M costs multiplied by the total energy generated.

3.4.2 Wind generation

An island can have different wind technology systems connected to it depending on its characteristics. These possibilities can be floating off-shore, founded off-shore and on-shore.

The three wind technologies share the same equations and module structure, and they are all presented at once in this section. The only difference among the three wind modules are the inputs provided by the user, such as: design parameters, costs, available space, state of the current installations.

Wind generation model

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Previously, in deliverable D1.2 (Ayesa Advanced Technologies, 2021), a representation of the general wind technology model was provided. It specifies that the power generation from wind can be determined by [Equation 6].

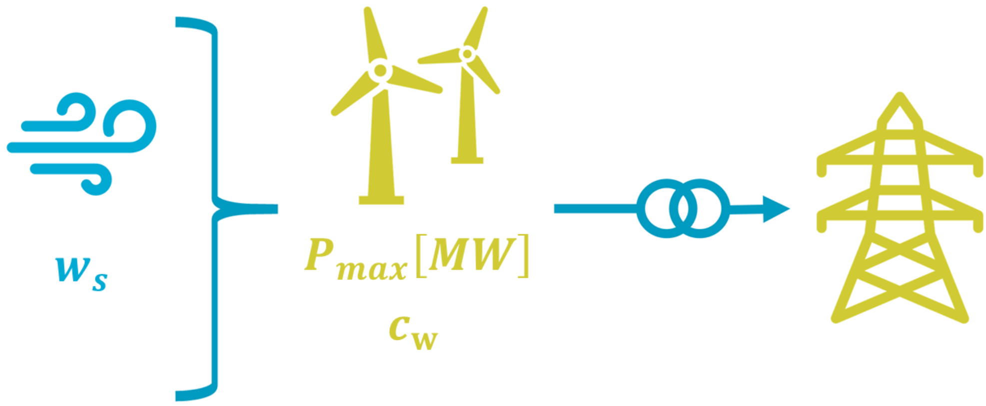

Figure 4. Energy hub model for wind generation.

$$P_{max,w} \cdot c_w \cdot w_s(t);\ \forall t \qquad \text{[Equation 6]}$$

Being the next equations the expression for each wind technology:

$$P_{onshore}(t) = P_{max,onshore} \cdot c_{onshore} \cdot w_s(t);\ \forall t \qquad \text{[Equation 7]}$$

$$P_{floating}\ (t) = P_{max,floating} \cdot c_{floating} \cdot w_s(t);\ \forall t \qquad \text{[Equation 8]}$$

$$P_{foundation}(t) = P_{max,foundation} \cdot c_{foundation} \cdot w_s(t);\ \forall t \qquad \text{[Equation 9]}$$

Where

- $P_{onshore}(t)$ the output power from the on-shore wind turbine [kW].
- $P_{floating}(t)$ the output power from the floating off-shore wind turbine [kW].
- $P_{foundation}(t)$ the output power from the founded off-shore wind turbine [kW].

Parameters

Design parameters

- $c_{onshore}$ piecewise linear function that define the on-shore windmills generation, given $w_{s,onshore}$ (t)
- $c_{floating}$ piecewise linear function that defines the off-shore floating windmills generation, $w_{s,floating}$ (t)
- $c_{floundation}$ piecewise linear function that defines the off-shore foundation windmills generation, $w_{s,foundation}$ (t).

  All these piecewise linear functions are defined in the same way, by the following equations:

  $$if\ [w_s < v_0] \rightarrow c_w = 0$$

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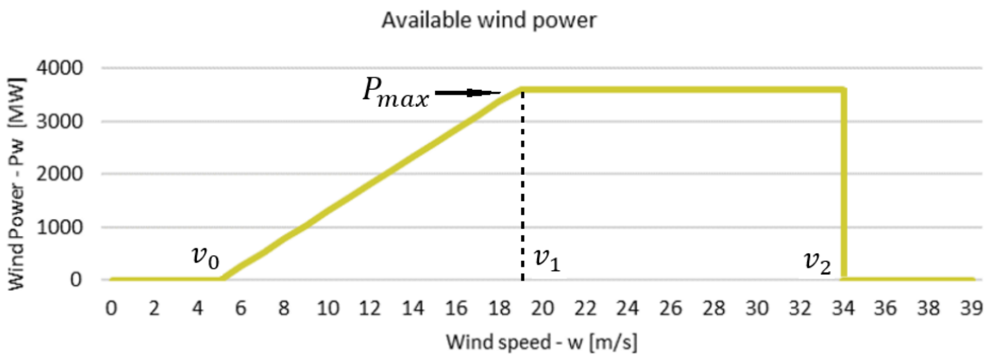
$$if\ [v_0 \leq w_s < v_1] \rightarrow c_w = \frac{1}{v_1 - v_0} - \frac{v_0}{(v_1 - v_0) \cdot w_s}$$
$$if\ [v_1 \leq w_s < v_2] \rightarrow c_w = \frac{1}{w_s}$$

Where:

- v_0 [m/s] is the minimum wind speed to make the windmills work.
- v_1 [m/s] is the optimal wind speed, or in other words the minimum wind speed that will make the windmills generate the maximum power.
- v_2 [m/s] is the maximum wind speed at which the windmills can work. If the registered wind speed is higher the wind farm must be turned off.



Available space

- $s_{inst,onshore}$ area taken by one kW of windmill on-shore installation
- $s_{inst,floating}$ area taken by one kW of windmill floating off-shore installation
- $s_{inst,foundation}$ area taken by one kW of windmill foundation off-shore installation
- $s_{tot,onshore}$ total area available for onshore windmills installations
- $s_{tot,floating}$ total area available for floating windmills installations
- $s_{tot,foundation}$ total area available for foundation windmills installations

State of the current installations

- $Installed_{onshore}$ [kW] size of the present installation on the island
- $Installed_{floating}$ [kW] size of the present installation on the island
- $Installed_{foundation}$ [kW] size of the present installation on the island

Costs

These are the costs of the installations, calculated per kW in the case of installation costs, and per kWh in the case of O&M costs.

Operational costs are also included. The cost of using the energy generated by the prosumers to satisfy the grid's demand, instead of using it for self-consumption.

- $C_{inst,onshore}$ [€/kW] is the cost associated to the installation of the onshore windmills.
- $C_{inst,floating}$ [€/kW] is the cost associated to the installation of the offshore floating windmills.
- $C_{inst,foundation}$ [€/kW] is the cost associated to the installation of the offshore

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foundation windmills.

- $C_{O\&M,onshore}$ [€/kWh] is the operational and maintenance cost associated to the onshore windmills.
- $C_{O\&M,floating}$ [€/kWh] is the operational and maintenance cost associated to the offshore floating windmills.
- $C_{O\&M,foundation}$ [€/kWh] is the operational and maintenance cost associated to the offshore foundation windmills.

Variables of the model

As with photovoltaic technology, P_{max} is the only variable that must be optimized to determine the size of each wind farm.

$$P_{max,onshore} \geq 0 \quad \text{[Equation 10]}$$

Peak power of windmill onshore installation.

$$P_{max,floating} \geq 0 \quad \text{[Equation 11]}$$

Peak power of windmill floating installation.

$$P_{max,foundation} \geq 0 \quad \text{[Equation 12]}$$

Peak power of windmill foundation installation.

Internal constrains

The physical constrains associated to this module are formulated as follows:

$$Installed_{onshore} \leq P_{max,onshore} \leq S_{tot,onshore}/S_{inst,onshore} \quad \text{[Equation 13]}$$

$$Installed_{floating} \leq P_{max,floating} \leq S_{tot,floating}/S_{inst,floating} \quad \text{[Equation 14]}$$

$$Installed_{floundation} \leq P_{max,floundation} \leq S_{tot,floundation}/S_{inst,floundation} \quad \text{[Equation 15]}$$

These are the only internal constraints of each wind module. They combine, just like with the solar park module, the present installation constraint, and the spatial one, by defining an interval for the sizing variables.

Contribution to the energy balance

The following equations model the generation of the wind farm at each timestep

$$\begin{gathered} P_{onshore}(t) = P_{max,onshore} \cdot c_{onshore} \cdot w_{s,onshore}(t) \\ P_{floating}(t) = P_{max,floating} \cdot c_{onfloating} \cdot w_{s,floating}(t) \\ P_{foundation}(t) = P_{max,foundation} \cdot c_{onfoundation} \cdot w_{s,foundation}(t) \end{gathered} \quad \text{[Equation 16]}$$

and they are the contribution to the energy balance of the island.

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Contribution to the objective function

The contribution to the objective function is, as usual, the sum of installation costs and maintenance costs. It is defined by the following equations:

On-shore

$$C_{inst,onshore} \cdot (P_{max,onshore} - Installed_{onshore}) + \sum_{t=1}^{T} C_{O\&M,onshore} \cdot P_{onshore}(t) \cdot (\boldsymbol{HxT})$$ [Equation 17]

Off-shore floating

$$C_{inst,\boldsymbol{floating}} \cdot (P_{max,\boldsymbol{floating}} - Installed_{\boldsymbol{floating}}) + \sum_{t=1}^{T} C_{O\&M,\boldsymbol{floating}} \cdot P_{\boldsymbol{floating}}(t) \cdot (\boldsymbol{HxT})$$ [Equation 18]

Off-shore foundation

$$C_{inst,\boldsymbol{foundation}} \cdot (P_{max,\boldsymbol{foundation}} - Installed_{\boldsymbol{foundation}}) + \sum_{t=1}^{T} C_{O\&M,\boldsymbol{foundation}} \cdot P_{\boldsymbol{foundation}}(t) \cdot (\boldsymbol{HxT})$$ [Equation 19]

Being HxT the number of hours in a timestep.

3.4.3 Li-ion storage

The third module is related to Li-ion battery storages. It is the first of the storage modules and it is recommended to activate it especially with the solar park option, since it is virtually impossible to install solar panels without a batteries storage system.

Li-ion battery storage model

Figure 5 shows a representation of the Li-ion battery storage model. In this figure one can see the energy flow through the battery.

Figure 5. Energy hub model for Li-ion battery

Where

- $B_k(t)$ kWh exchanged energy by the battery k at time t
- $E_k(t)$ kWh energy stored by battery at time t

This model comes from the previous deliverable (D.1.2), and the relation between the quantity is

$$E_k(t) = e(t) \cdot B_k(t) \quad \forall\, t = 1, \dots, T$$

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Where $e(t)$ represents the efficiency of the battery, and it can assume two values:

- $e(t) = e_{discharge}$ if $B_k(t) < 0$ if the batteries are discharging. Default value is 0.7.
- $e(t) = e_{charge}$ if $B_k(t) > 0$ if the batteries are charging. Default value is $\frac{1}{0.9} = 1.111$.

This way the above equation holds for charge and in discharge mode. However, the discontinuity of the efficiency value makes it impossible to use it as it is in a LP model, since it is not linear.

To make this work, a mathematical artifice needs to be put in place, using an auxiliary variable representing $\max(0, B_k(t))$ the positive part of the energy flow. Define such auxiliary variable in a linear environment is impossible without the aid of a boolean variable. A boolean variable is an integer variable that can only assume values 0 and 1. Using a boolean variable and six additional constraints the auxiliary variable can be defined, making it possible to use different efficiency values depending on the direction of the energy flow.

This artifice changes the problem from LP to MILP, raising the complexity significantly. It has been implemented and used for a certain period, however the toll on computational time is too high to justify it, and it made it impossible for the solver to reach a solution of the full problem in an acceptable time.

For these reasons, there is a single value of efficiency for charge and discharge, which makes the model less accurate, but it is an error that can be accounted for in the phase of study of the results and by an oversizing process.

See the final paragraph of this section for more details on the dismissed method.

Parameters

Design parameters

These are parameters that characterise the storage systems.

- $e_{battery}$ Li-ion batteries efficiency. Default value is = 1.0
- $E_{0,battery}$ Li-ion batteries initial charge. Default value is = 0.0

Available space

- $S_{inst,battery}$ [m^2/kWh] space (surface) taken by one battery installation
- $S_{tot,battery}$ [m^2] total space (surface) available for Li-ion batteries installations

State of the current installations

- $Installed_{battery}$ [kWh] size of the present installation on the island

Cost

- $C_{inst,battery}$ [€/kWh] installation cost. Default value is = 295.75
- $C_{O\&M,battery}$ [€/kWh] operation and maintenance cost. Default value is =0.0

Variables

This module has one sizing variable:

$$E_{max,battery} \geq 0 \text{ [kWh]} \qquad \text{[Equation 20]}$$

And the energy flow operational variables:

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$$P_{oper,battery}(t) \in \mathbb{R}\ [\mathrm{kW}]$$ [Equation 21]

Unlike the previous generation modules, where the variable was just one, in this case we are defining $T+1$ variables, where T is the number of timesteps of the problem. Clearly the energy flow variables are not sizing ones, but it is necessary to add them, in order to give the solver the freedom to find the optimal usage of the storage system.

- when $P_{oper,battery}(t) > 0$ the batteries are discharging and injecting energy into the grid
- when $P_{oper,battery}(t) < 0$ the batteries are charging.

If we were to only define the sizing variable, just like with the generation modules, the energy flow in and out of the batteries would be fixed. In that case the only thing the solver can do is minimise the size of the batteries allowing the fixed energy flows to take place. By defining all these operational variables on the contrary, we are letting the solver explore all the usage possibilities for the storage system and pick the best one. This way we will also have a justification of the sizing result, and an explanation of how the storage system was optimally used.

Internal constrains

First, let us define the State of Charge (SOC) of the storage systems at time t, representing the level of charge of the battery at every timestep. This is not a constraint, it is just a quantity that will help define the actual constraints and understand why they are defined in such way.

$$\begin{aligned} \boldsymbol{SOC_{battery}(t)} &= \boldsymbol{SOC_{battery}(t-1)} \\ &\quad - \left(\boldsymbol{e_{battery} \cdot P_{oper,battery}(t)} \right) \cdot \boldsymbol{(HxT)} \\ &= -\left(\boldsymbol{e_{battery} \cdot \sum_{i=1}^{t} P_{oper,battery}(i)} \right) \cdot \boldsymbol{(HxT)} \\ &\quad + \boldsymbol{E_{0,battery}} \end{aligned}$$ [Equation 22]

In this expression the state of charge at time t is defined as the sum of the state of charge of the previous timestep, and the energy following through the battery at time (t) (could be entering or exiting). To define this energy, the operational power variable is multiplied by the efficiency and by HxT (hours per timestep).

By recursively applying the same formula to $SOC_{battery}(t-1)$, we end up with the sum over all the timesteps up until t of the energy flowing through the battery. Energy at timestep 0 is equal to the initial charge $E_{0,battery}$.

With the SOC defined, we can proceed to shape the constraints that will model the storage system.

$$SOC_{battery}(t) \geq 0 \forall\ t = 1 \dots T$$ [Equation 23]

At each timestep the stored energy must be non-negative.

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$$E_{max,battery} \geq SOC_{battery}(t)\ \forall\ t = 1 \dots T \quad \text{[Equation 24]}$$

Batteries installation size must be greater than stored energy at each timestep.

$$e_{battery} \cdot P_{oper,battery}(t) \cdot HxT \leq SOC_{battery}(t-1)\ \forall\ t = 1 \dots T \quad \text{[Equation 25]}$$

At each timestep, the energy that the batteries are injecting into the grid must be smaller than the total amount stored. Note that in the case of the battery being charging at time t, the constraint is always fulfilled (a negative quantity is equal or lower than a non-negative quantity).

Also, the usual constraint merging state of the current installations and spatial limitations is present:

$$Installed_{battery} \leq E_{max,battery} \leq S_{tot,battery}/S_{inst,battery} \quad \text{[Equation 26]}$$

Contribution to the energy balance

The contribution to the energy balance is simply the value of the operational variable at time t:

$$P_{oper,battery}(t) \quad \text{[Equation 27]}$$

As specified before, this quantity can assume positive values (when batteries are discharging), and negative values (when batteries are charging), unlike consumption and generation.

Contribution to the objective function

The contribution of the Li-ion batteries to the objective function can be modelled following equation below:

$$\boldsymbol{C_{inst,battery} \cdot (E_{max,battery} - Installed_{battery}) + \left(C_{O\&M,battery} \cdot \sum_{t=1}^{T} P_{oper,battery}(t) \right) \cdot (HxT)} \quad \text{[Equation 28]}$$

Auxiliary/Boolean artifice (deprecated)

Usually the charging and discharging efficiency have different values, and the battery being in charge or discharge mode is given by the sign of the operational variable $P_{oper,battery}(t)$. Hence in different expressions this variable needs to be scaled by two different factors, depending on its sign. Such operation can be made into a linear expression, but only with the help of two additional operational variables

- $P_{oper,battery}(t) \in \mathbb{R}$ [kW]. Power through the Li-ion batteries at time t.
- $X_{charge/discharge}(t) \in \{0,1\}$. Auxiliary binary variable (must be shaped in a way such that $X_{charge/discharge}(t) = 0$ if batteries are discharging, $X_{charge/discharge}(t) = 1$ if batteries are charging).

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- $P_{aux,battery}(t) \geq 0$. Auxiliary power variable ((must be shaped in a way such that $P_{aux,battery}(t)$= $P_{oper,battery}(t)$ if batteries are discharging, $P_{aux,battery}(t)$= 0 if batteries are charging).
- $e_{charge,battery}$ Li-ion batteries charging efficiency. Default value is = 0.7
- $e_{discharge,battery}$ Li-ion batteries discharging efficiency. Default value is = 1/0.9

Let us shape the behaviour of these two auxiliary variables: the aim is to make $P_{aux,battery}(t) = P_{oper,battery}(t) \geq 0$ if batteries are discharging, and $P_{aux,battery}(t) = 0$ if batteries are charging. In other words, $P_{aux,battery}(t) = max(P_{oper,battery}, 0)$, and this is achieved through the following 6 auxiliar constraints:

1. $P_{aux,battery}(t) - P_{max,battery} \cdot X_{charge/discharge}(t) \leq 0$
2. $-P_{aux,battery}(t) + P_{min,battery} \cdot X_{charge/discharge}(t) \leq 0$
3. $-P_{oper,battery}(t) + P_{aux,battery}(t) - P_{min,battery} \cdot X_{charge/discharge}(t) \leq P_{min,battery}$
4. $P_{oper,battery}(t) - P_{aux,battery}(t) + P_{max,battery} \cdot X_{charge/discharge}(t) \leq P_{max,battery}$
5. $-P_{oper,battery}(t) - P_{min,battery} \cdot X_{charge/discharge}(t) \leq -P_{min,battery}$
6. $P_{oper,battery}(t) - P_{max,battery} \cdot X_{charge/discharge}(t) \leq 0$

Through these equations we have obtained the following:

- Discharged power at time t: $P_{aux,battery}(t)$
- Charged power at time t: $P_{aux,battery}(t) - P_{oper,battery}(t)$

In this case the State of Charge (SOC) of the storage systems at time t, representing the level of charge of the battery, would be defined as follows:

$$\begin{aligned}\boldsymbol{SOC_{battery}(t)} &= \boldsymbol{SOC_{battery}(t-1)} \\ &\quad - \left(\boldsymbol{e_{charge,battery} \cdot P_{oper,battery}(t) - (e_{charge,battery} - e_{discharge,battery})} \right. \\ &\quad \left. \boldsymbol{\cdot P_{aux,battery}(t)} \right) \cdot \boldsymbol{(HxT)} \\ &= \left(\boldsymbol{e_{charge,battery} \cdot \sum_{i=1}^{t} P_{oper,battery}(i) - (e_{charge,battery} - e_{discharge,battery})} \right. \\ &\quad \left. \boldsymbol{\cdot \sum_{i=1}^{t} P_{aux,battery}(i)} \right) \cdot \boldsymbol{(HxT) + E_{0,battery}}\end{aligned}$$

In the final version of the model this formulation is not implemented because of computational issues that arise due to the time-dependent Boolean variables.

3.4.4 Hydrogen storage

Hydrogen storage systems are divided into electrolyser, storage tanks, and fuel cell. Since the *charging* and *discharging* devices can in theory work at the same time, the storage model will be different from the Li-ion battery one. In particular, in this case the double efficiency for charging and discharging can be implemented without increasing the complexity of the model.

Hydrogen storage model

The following figure represents the scheme of a typical hydrogen storage system.

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Figure 6. Energy hub model concept for hydrogen storage

Being

- $P_e(t)$ the input power on the electrolyser at time t.
- $E_{H2}(t)$ the energy delta stored on the system at time t (can be positive or negative).
- $P_{fc}(t)$ the output power on the fuel cell at time t.

These quantities are related by the following formula:

$$E_{H2}(t) = e_{electrolyser} \cdot P_e(t) - e_{fuel\ cell} \cdot P_{fc}(t)$$

Parameters

Design parameters

- $e_{electrolyser}$ electrolyser charging efficiency. Default value is = 0.47
- $e_{fuel\ cell}$ fuel cell discharging efficiency. Default value is = 1/0.65
- $E_{0,H2}$ [Kg] hydrogen initial charge. Default value is = 0
- $r_{energy,H2}$ [kWh/kg] usable energy in 1kg of H2. Default value is = 33.33

Available space

- $S_{inst,tank}$ [m^2/kW] space (surface) taken by the H2 tank installation
- $S_{inst,electrolyser}$ [m^2/kW] space (surface) taken by the electrolyser installation
- $S_{inst,fuelcell}$ [m^2/kW] space (surface) taken by the fuel cell installation

- $S_{tot,H2}$ [m^2] total space (surface) available for the H2 storage system installation

Cost

- $C_{inst,electrolyzer}$ [€/kW] Default value is = 9039
- $C_{inst,fuel\ cell}$ [€/kW] Default value is = 12276
- $C_{inst,H2\ tank}$ [€/kWh] Default value is = 1756
- $C_{O\&M,electrolyzer}$ [€/kWh] Default value is =0.0
- $C_{O\&M,fuel\ cell}$ [€/kWh] Default value is = 0.0
- $C_{O\&M,H2\ tank}$ [€/kWh] Default value is = 0.0

Variables of the model

In the case of the hydrogen-based system, since it is possible to charge and discharge at the same time, we have different variables that represent the energy flow. All of them are included on hydrogen generation group. The rest of the variables of the model are grouped like the previous technologies.

Sizing variable

$$m_{max,stored\ H2} \quad \text{[Equation 29]}$$

[kg] Size of the H2 tank.

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$$P_{max,electrolyzer} \quad \text{[Equation 30]}$$

[kW] Size of the electrolyser

$$P_{max,fuel\ cell} \quad \text{[Equation 31]}$$

[kW] Size of the fuel cell

Operational Variables

$$P_e(t) \geq 0 \quad \text{[Equation 32]}$$

[kW] Power entering the electrolyser at time t.

$$P_{fc}(t) \geq 0 \quad \text{[Equation 33]}$$

[kW] Power exiting the tank at time t.

In total this module adds $2T + 3$ variables to the model, where T is the number of timesteps of the model.

Internal constrains

The storage system is modelled following the same principles and equations used for the Li-ion batteries. However, since in theory it is possible to charge the tanks while the fuel cells are running, two operational variables are used instead of one. Each operational variable (charging and discharging) can be multiplied separately by its own efficiency.

Defining the state of charge of the tanks for the hydrogen system we have that:

$$\begin{aligned} SOC_{H2}(t) &= E_{0,H2} + SOC_{H2}(t-1) - \left(e_{electrolyzer} \cdot P_e(t) - e_{fuel\ cell} \cdot P_{fc}\right) \\ &\cdot (HxT) \\ &= \left(e_{electrolyzer} \cdot \sum_{i=1}^{t} P_e(i) - e_{fuel\ cell} \cdot \sum_{i=1}^{t} P_{fc}(i)\right) \cdot (HxT) \\ &+ E_{0,H2} \end{aligned} \quad \text{[Equation 34]}$$

Just like with the Li-ion batteries, the SOC is useful to define the following constraints:

$$SOC_{H2}(t) \geq 0 \ \forall\, t = 1 \dots T \quad \text{[Equation 35]}$$

At each timestep the stored energy must be non-negative.

$$m_{max,stored\ H2} \cdot r_{energy,H2} \geq HxT \cdot SOC_{H2}(t)\ \forall\, t = 1 \dots T \quad \text{[Equation 36]}$$

Hydrogen tank size must be greater than stored energy at each timestep. The ratio $r_{energy,H2}$ is used to convert mass into available energy.

$$e_{fuel\ cell} \cdot P_{fc}(t) \cdot HxT \leq SOC_{H2}(t-1)\ \forall\, t = 1 \dots T \quad \text{[Equation 37]}$$

At each timestep, the energy that the batteries are injecting into the grid must be smaller than the total amount stored.

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$$e_{electrolyzer} \cdot P_e(t) \cdot HxT \leq P_{max,electrolyzer} \; \forall \; t = 1 \dots T$$ [Equation 38]

At each timestep, the power entering the electrolyser must be smaller than its size.

$$e_{fuel\ cell} \cdot P_{fc}(t) \cdot HxT \leq P_{max,fuel\ cell} \; \forall \; t = 1 \dots T$$ [Equation 39]

At each timestep, the power exiting the fuel cell must be smaller than its size.

Just like with the previous modules, available space is considered by the constraints.

$$S_{inst,tank} \cdot m_{max,stored\ H2} + S_{inst,electrolyser} \cdot P_{max,electrolyser} + S_{inst,fuelcell} \cdot P_{max,fuelcell} \leq S_{tot,H2}$$ [Equation 40]

Contribution to the energy balance

The following quantity is the contribution to the energy balance of the hydrogen storage module, which is the difference between what is being injected in the grid, and what is being stored in the tanks through the electrolyser.

$$P_{fc}(t) - P_e(t)$$ [Equation 41]

Ideally in the real system, when one of these values is positive, the other one equals to zero. However there are some situations in which it is both charging and discharging at the same time, and thus in the model it is also possible.

Contribution to the objective function

The contribution of the hydrogen storage systems to the objective function can be modelled following quantity:

$$C_{inst,electrolyser} \cdot P_{max,electrolyser} + C_{inst,tank} \cdot m_{max,stored\ H2} \cdot r_{energy,H2} + C_{inst,fuelcell} \cdot P_{max,fuelcell} + \left(\sum_{t=1}^{T} C_{O\&M,electrolyzer} \cdot P_e(t) + \sum_{t=1}^{T} C_{O\&M,tank} \cdot P_{fc}(t) + \sum_{t=1}^{T} C_{O\&M,fuelcell} \cdot P_{fc}(t) \right) \cdot (HxT)$$ [Equation 42]

Note that to compute the maintenance cost of the tanks, the charged energy is used, as an approximation.

3.4.5 Existing interconnection

The existing interconnections make it possible to meet the energy demand between the island and the mainland through import or export. This is the module that was presented also in the previous deliverable, named just *Interconnection*. However, in the optimisation model two interconnection modules are present, the first one is to model an already existing interconnection, the second one evaluates the possibility to install a new interconnection.

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Existing interconnection model

Figure 7 shows the energy hub model of this module, where $\boldsymbol{E_{existing\ inter}}$ represents the energy flow through the interconnection wire.

Figure 7. Energy hub model concept for existing interconnection

Where

- $E_{existing,inter}(t) = P_{existing\ inter,oper}\ (t) \cdot HxT$ represents the energy flowing through the cable.

Parameters

Design parameters

- $P_{max,existing\ inter} > 0$ [kW] Maximum power entering the island through the cable. Default value = 10000
- $P_{min,existing\ inter} < 0$ [kW] Maximum power exiting the island through the cable. Default value = -10000

Cost

- $C_{buying\ inter}$ [€/kWh] Default value is = 0.6

Variables of the model

$$\boldsymbol{P_{existing\ inter,oper}\ (t)} \in \mathbb{R} \quad \text{[Equation 43]}$$

Are the operational variables and can take positive values (when buying energy) or negative values (when selling).

$$\boldsymbol{P_{existing\ inter,aux}\ (t) > 0} \quad \text{[Equation 44]}$$

Are auxiliary variables, needed to apply the buying cost only when the operational variables are positive. Just like with batteries efficiency, to multiply a time dependent variable by two different values depending on its sign, leads to non-linearity. In this case however it can be solved without the necessity of any Boolean variable. This auxiliary variable is used to model the function

$$\boldsymbol{P_{existing\ inter,aux}\ (t)} = \max\left(0, \boldsymbol{P_{existing\ inter,oper}\ (t)}\right)$$

through the constraints.

In total this module adds $2T$ variables to the model, where T is the number of timesteps of the model.

Internal constrains

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The interconnection module is fairly simple to model

$$P_{min,existing\ inter} \leq P_{existing\ inter}(t) \leq P_{max,existing\ inter}\ \forall\ t = 1 \dots T$$ [Equation 45]

The power through the cable cannot be higher than the maximum capacity of the cable, in neither direction.

$$P_{existing\ inter,aux}\ (t) \geq P_{existing\ inter,oper}\ (t)\ \forall\ t = 1 \dots T$$ [Equation 46]

The auxiliary variable cannot be lower than the operational one. The expected behaviour is

- $P_{existing\ inter,aux}\ (t) = P_{existing\ inter,oper}\ (t)$ if $P_{existing\ inter,oper}\ (t) > 0$
- $P_{existing\ inter,aux}\ (t) = 0\ (t)$ if $P_{existing\ inter,oper}\ (t) \leq 0$

and it is only natural for the auxiliary variable to behave like this, since it will be the one used in the objective function. Still, a warning will appear if the auxiliary variable does anything different from this.

Contribution to the energy balance

The only contribution to the energy balance constraints is the value of the operational variable

$$P_{existing\ inter,oper}\ (t)$$ [Equation 47]

It can be positive (when buying energy) or negative (when sending energy to the mainland).

Contribution to the objective function

The contribution of this module to the objective function is computed using the auxiliary variable.

$$\left(C_{existing\ inter} \sum_{t=1}^{T} P_{existing\ inter,aux}(t)\right) \cdot (HxT)$$ [Equation 48]

This way the quantity appearing in the objective function is the total amount of energy bought from the mainland. Initially the energy sold was discounted from the final amount, however this would make the interconnection module the only possible choice for the solver. In fact, provided that the amounts of energy bought and sold were pretty much the same, the interconnection would substantially have the same functioning of a battery, but without any restriction nor installation cost, and it would be chosen over a battery every time.

However, the interconnection module is supposed to be among the most penalizing ones if we think in terms of decarbonization and independence of the island. For this reason, the auxiliary variable method was implemented, multiplying the cost only by the amount of energy bought.

3.4.6 New interconnection

Previously, it has mentioned that there is the possibility to install an interconnection system with another hub (mainland). The new module is necessary in case the island has no interconnection and needs one, or if it requires additional power supply. In this case the

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solver can choose if to install a new cable, or not. The functioning of the module is substantially the same as the existing interconnection one.

New interconnection model

In Figure 8 it can be seen a combination of the two interconnection models, the existing and the new one.

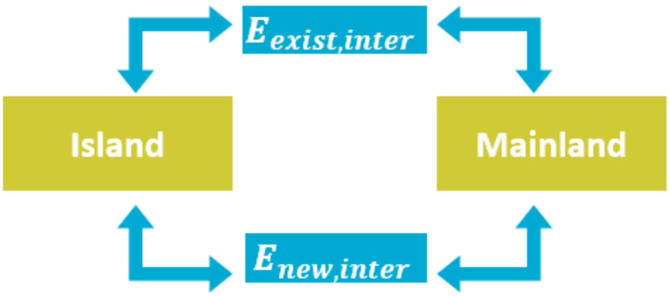

Figure 8. Energy hub model concept for new interconnection

Where

- $E_{new,inter}(t) = P_{new\ inter,oper}\ (t) \cdot HxT$ represents the additional energy flowing through the new interconnection cable.

Parameters

Design parameters

- $P_{max,new\ inter} > 0$ [kW] Maximum power entering the island through the cable. Default value = 10000
- $P_{min,new\ inter} < 0$ [kW] Maximum power exiting the island through the cable. Default value = -10000

Cost

- $C_{buying\ intercon}$ [€/kWh] cost of the energy. Default value is = 0.6

Variables of the model

$$\boldsymbol{P_{new\ inter,oper}\ (t)} \in \mathbb{R} \qquad \text{[Equation 49]}$$

Are the operational variables and can take positive values (when buying energy) or negative values (when selling).

$$\boldsymbol{P_{new\ inter,aux}\ (t) > 0} \qquad \text{[Equation 50]}$$

Are auxiliary variables, needed to apply the buying cost only when the operational variables are positive. Just like with batteries efficiency, to multiply a time dependent variable by two different values depending on its sign, leads to non-linearity. In this case however it can be solved without the necessity of any Boolean variable. This auxiliary variable is used to model the function

$$\boldsymbol{P_{new\ inter,aux}\ (t)} = \max\left(0, \boldsymbol{P_{new\ inter,oper}\ (t)}\right)$$

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through the constraints.

$$B_{new\ inter} \in \{0,1\}$$ [Equation 51]

Boolean variable, True ($=1$) if the solution requires the installation of a new interconnection.

In total this module adds $2T+1$ variables to the model, where T is the number of timesteps of the model.

Internal constrains

Same constraints of the existing interconnection module, but with the addition of the Boolean variable

$$P_{min,new\ inter} \cdot B_{new\ inter} \leq P_{new\ inter}(t) \leq P_{max,new\ inter} \cdot B_{new\ inter}$$ [Equation 52]

The power through the cable cannot be higher than the maximum capacity of the cable, in neither direction. If the cable is not installed, and $B_{new\ inter}=0$, these constraints force the operational variable to be equal to zero at every timestep.

$$P_{new\ inter,aux}(t) \geq P_{new\ inter,oper}(t)\ \forall\ t=1 \dots T$$ [Equation 53]

The auxiliary variable cannot be lower than the operational one. The expected behaviour is

- $P_{new\ inter,aux}(t) = P_{new\ inter,oper}(t)$ if $P_{new\ inter,oper}(t) > 0$
- $P_{new\ inter,aux}(t) = 0\ (t)$ if $P_{new\ inter,oper}(t) \leq 0$

and it is only natural for the auxiliary variable to behave like this, since it will be the one used in the objective function. Still, a warning will appear if the auxiliary variable does anything different from this.

Contribution to the energy balance

The only contribution to the energy balance constraints is the value of the operational variable

$$P_{new\ inter,oper}(t)$$ [Equation 54]

It can be positive (when buying energy) or negative (when sending energy to the mainland).

Contribution to the objective function

The contribution of this module to the objective function is computed using the auxiliary variable.

$$\left(C_{new\ inter} \sum_{t=1}^{T} P_{new\ inter,aux}(t)\right) \cdot (HxT)$$ [Equation 55]

This way the quantity appearing in the objective function is the total amount of energy bought from the mainland. Same as *existing interconnection*, see section above for more

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information.

3.4.7 Prosumers

The prosumers' module is one of the most complicated, and it was not present in the initial definition of the island's systems in D.1.2. It models the possibility of installing PV panels on private buildings, hence it includes solar generation and Li-ion batteries at the same time. The battery installation, however, are not mandatory to install with the panels. If they are installed however, the model takes for granted that they are connected to the grid. This implies that they can be charged not only with the energy produced by the panels, but also through the grid. The solver will thus be able to optimise the general behavior of the prosumers' batteries, regardless of the actual prosumers' needs and will. This is an approximation that aims to model the DR functionality. In fact, through the app the prosumers will be able to respond to the island grid's needs.

Prosumers model

A simple example is showed in Figure 9, where E_{pros} represents the whole energy provided by PV panels installed on prosumers installations and batteries, if they are present.

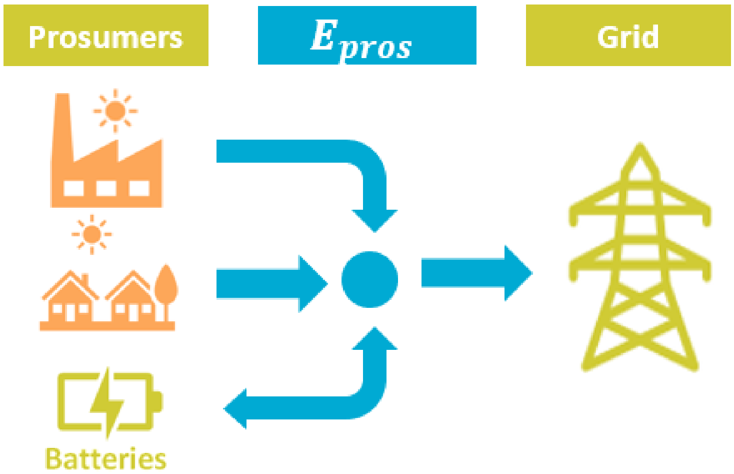

Figure 9. Energy hub model concept for prosumers

Parameters

Design parameters

- $e_{prosumer}$ prosumer batteries efficiency. Default value is = 1.0
- $E_{battery\ limit,pros}$ [kWh] the maximum size of batteries per panel installed
- $P_{p,pros}$ [kW] denotes the peak power of a single panel (provided by the manufacturer)

Regarding the weather-corrected factor the terms used are the following:

- $H(t)$ [W/m^2] determines the measured plane of array (POA) irradiance. It is a time-dependent input and needs to be given to the model as an array.
- $G_{ref,pros}$ [W/m2] established the irradiance at standard test conditions (STC). Default value=1000.
- $T_{m,pros}$ [°C] is the cell temperature from PV panel. In case the user does not have this parameter, it will not be factored in the generation equation.
- $T_{ref,pros}$ [°C] represents the temperature at standard test condition.

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- γ_{pros} [1/°C] is temperature coefficient for power that corresponds to the installed modules (must be < 0).

And respect to the degradation factor, parameters d and n must be obtained through the datasheet from manufacturer as follow:

- $d_{pros} = 1 - \sqrt[y]{\eta_y}$ represents de degradation over the years.
    - η_y [kW] is the final guaranteed power performance established by manufacturer.
    - y is the final year established by manufacturer.
- $n_{pros} = \frac{c_d - c_c}{365}$, on the other hand, represents the period of the degradation.
    - c_d indicates the last day of the analysis
    - c_c is the commissioning day.

Available spaces

- $S_{tot,pros}$ [m^2] is the total available space on the island to install prosumers' solar panels.
- $S_{kW,pros}$ [m^2/kW] is the space occupied by a single kW of installation.

State of the current installation

- $Installed_{PV,pros}$ [kW] Power installed previously on the island
- $Installed_{battery,pros}$ [kWh] size of the present installation on the island

Cost

- $C_{inst,prosPV}$ [€/kW] is the installation cost of a single panel
- $C_{O\&M,prosPV}$ [€/kWh] is the operating and maintenance cost per kWh produced
- $C_{inst,pros\ battery}$ [€/kWh] installation cost of one kWh of batteries. Default value is = 295.75
- $C_{O\&M,pros\ battery}$ [€/kWh] operation and maintenance cost per kWh. Default value is =0.0

Variables of the model

The prosumers module has two sizing variables, one for the solar panel installation and the other one for the batteries

$$\boldsymbol{P_{0,pros} \geq 0}$$ [Equation 56]

$$E_{max,pros} \geq 0 \text{ [kWh]}$$ [Equation 57]

Just like in the battery module, there are the operational variables representing the energy flow in and out of the batteries

$$P_{oper,pros}(t) \in \mathbb{R} \text{ [kW]}$$ [Equation 58]

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In total this module adds $T+2$ variables to the model, where T is the number of timesteps of the model.

Internal constrains

The internal constraints are the same constraints modelling the PV park module and the Li-ion batteries module, with the addition of a single constraint relating the two parts. This further restriction limits the total size of the prosumers' batteries installation to a quantity determined by the panels installation. In other words, the storage cannot be bigger than the maximum allowed by the number of the panels:

$$E_{max,pros} \leq E_{battery\ limit,pros} \cdot (\boldsymbol{P_{0,pros}}/P_{p,pros})$$ [Equation 59]

Current installation and spatial constraints:

$$Installed_{prosPV} \leq P_{0,pros} \leq S_{tot,pros}/S_{kW,pros}$$ [Equation 60]

$$Installed_{battery,pros} \leq E_{max,pros}$$ [Equation 61]

All the remaining constraints are formulated exactly like the ones in the batteries' module, although with the prosumers' specific parameters:

$$SOC_{pros}(t) \geq 0 \forall\ t = 1 \dots T$$ [Equation 62]

At each timestep the stored energy must be non-negative.

$$E_{max,pros} \geq SOC_{pros}(t)\ \forall\ t = 1 \dots T$$ [Equation 63]

Batteries installation size must be greater than stored energy at each timestep.

$$e_{pros} \cdot P_{oper,pros}(t) \cdot HxT \leq SOC_{pros}(t-1)\ \forall\ t = 1 \dots T$$ [Equation 64]

At each timestep, the energy that the batteries are injecting into the grid must be smaller than the total amount stored.

In all the constraints above, the State of Charge $SOC_{pros}(t)$ is defined as follows:

$$\boldsymbol{SOC_{pros}(t) = SOC_{pros}(t-1) - \left(e_{pros} \cdot P_{oper,pros}(t)\right) \cdot (HxT) = -\left(e_{pros} \cdot \sum_{i=1}^{t} P_{oper,pros}(i)\right) \cdot (HxT)}$$ [Equation 65]

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Contribution to the energy balance

The contribution to the energy balance restriction in this case is a combination of the energy generated by the panels, and the energy flow to and from the batteries of the panels. It is formulated the following way

$$P_{PV,pros}(t) + P_{oper,pros}(t) = P_{0,pros} \cdot \frac{H(t)}{G_{ref,pros}} [1 + \gamma_{pros}(T_{m,pros} - T_{ref,pros})](1 - d_{pros})^{n_{pros}} + P_{oper,pros}(t)$$ [Equation 66]

Contribution to the objective function

As usual, the contribution to the objective function is a combination of installation costs and maintenance costs, both for the solar panels part and the batteries part of the module.

$$\frac{C_{inst,prosPV} \cdot (P_{0,pros} - Installed_{PVpros})}{P_{p,pros}} + \left(C_{O\&M,prosPV} \cdot \sum_{t} P_{PV,pros}(t) \right) \cdot (HxT) + C_{inst,battery\ pros} \cdot (E_{max,pros} - Installed_{battery\ pros}) + \left(C_{O\&M,battery\ pros} \cdot \sum_{t=1}^{T} P_{oper,pros}(t) \right) \cdot (HxT)$$ [Equation 67]

Previous formulation (deprecated)

The prosumers one is the module that has gone through the most radical changes during the development of the program. The initial idea with this module was to divide the consumption timeseries in two parts: the potential prosumers consumption and the rest. With this diversification, there would have been the possibility to incentive prosumers' self-consumption, by adding a penalization cost whenever the energy generated by the prosumers' panels would have been used to satisfy the general consumption, and not the prosumers consumption.

Later, the prosumers consumption was divided once more between domestic prosumers and industrial prosumers. This would have given the end user the flexibility to differentiate between the domestic and industrial consumption patterns. The three different consumption timeseries were connected to each other by operational variables:

- $P_{oper,D2G}(t)$ domestic to grid operational variable. If positive, it represents the energy generated by the domestic prosumers that is going to be fed to the grid (hence not used for self-consumption) at time t. If negative, it represents the energy flowing from the grid to the houses of the prosumers at time t (generally meaning the prosumers generation is not sufficient).
- $P_{oper,I2G}(t)$ industrial to grid operational variable. Same functioning as $P_{oper,D2G}(t)$.

These variables would have to be multiplied by a different penalization cost depending on the sign of the variable, hence an auxiliary and a Boolean variable were needed to keep all the

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equations linear.

We report below the restrictions needed to model the **domestic** prosumers

1. $P_{aux,dom\ pros}(t) - P_{max,dom\ pros} \cdot X_{bool,dom\ pros}(t) \ \leq 0$
2. $-P_{aux,dom\ pros}(t) + P_{min,dom\ pros} \cdot X_{bool,dom\ pros}(t) \ \leq 0$
3. $-P_{oper,dom\ pros}(t) + P_{aux,dom\ pros}(t) - P_{min,dom\ pros} \cdot X_{bool,dom\ pros}(t) \ \leq -P_{min,dom\ pros}$
4. $P_{oper,dom\ pros}(t) - P_{aux,dom\ pros}(t) + P_{max,dom\ pros} \cdot X_{bool,dom\ pros}(t) \ \leq P_{max,dom\ pros}$
5. $-P_{oper,dom\ pros}(t) - P_{min,dom\ pros} \cdot X_{bool,dom\ pros}(t) \leq -P_{min,dom\ pros}$
6. $P_{oper,dom\ pros}(t) - P_{max,dom\ pros} \cdot X_{bool,dom\ pros}(t) \ \leq 0$

These restrictions above are the same auxiliary restrictions that were initially used in the Li-ion batteries storage module (Li-ion storage).

7. $SOC_{dom\ pros}(t) \geq 0\ \forall\ t = 1 \dots T$
8. $\bar{E}_{max,dom\ pros} \geq HxT\ \cdot SOC_{dom\ pros}(t)\ \forall\ t = 1 \dots T$
9. $e_{discharge,dom\ pros} \cdot P_{aux,dom\ pros}(t) \cdot HxT \leq SOC_{dom\ pros}(t-1)\ \forall\ t = 1 \dots T$

Where:

$$\boldsymbol{SOC_{dom\ pros}(t)} = SOC_{dom\ pros}(t-1) - \Big(e_{charge,dom\ pros} \cdot P_{oper,dom\ pros}(t) - \big(e_{charge,dom\ pros} - e_{discharge,dom\ pros}\big) \cdot P_{aux,dom\ pros}(t)\Big) \cdot (HxT) = \left(e_{charge,dom\ pros} \cdot \sum_{i=1}^{t} P_{oper,dom\ pros}(i) - \big(e_{charge,dom\ pros} - e_{discharge,dom\ pros}\big) \cdot \sum_{i=1}^{t} P_{aux,dom\ pros}(i) \right) \cdot (HxT) + E_{0,dom\ pros}$$

The state of charge is defined with the double efficiency (charge and discharge), through the auxiliary variable.

Moreover, the following auxiliary equations used to model the connection between the domestic consumption and the general consumption:

10. $P_{aux,D2G}(t) - P_{max,D2G} \cdot X_{bool,D2G}(t) \leq 0$
11. $-P_{aux,D2G}(t) + P_{min,D2G} \cdot X_{bool,D2G}(t) \leq 0$
12. $-P_{oper,D2G}(t) + P_{aux,D2G}(t) - P_{min,D2G} \cdot X_{bool,D2G}(t) \leq -P_{min,D2G}$
13. $P_{oper,D2G}(t) - P_{aux,D2G}(t) + P_{max,D2G} \cdot X_{bool,D2G}(t) \leq P_{max,D2G}$
14. $-P_{oper,D2G}(t) - P_{min,D2G} \cdot X_{bool,D2G}(t) \leq -P_{min,D2G}$
15. $P_{oper,D2G}(t) - P_{max,D2G} \cdot X_{bool,D2G}(t) \leq 0$

All these variables and constraints were repeated for the case of **industrial prosumers**.

The usage of these type of variables precluded the possibility to obtain results from timeseries longer than a month (1 hour granularity). Also, as good as it sounds to adapt the model to the consumption pattern of each category of prosumers, it is all but easy for the final user to provide consumption timeseries of buildings that will potentially install solar panels on their roof. Certainly, some degree of approximation would be used, risking to nullify the purpose of the artifices.

For these reasons, instead of pursuing a way to enhance the performance of the model, the decision was made to simplify the module to the version described initially.

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3.4.8 Mobility

The mobility module is different from all the previous ones, mostly because it does not add new variables and constraints to the model, but it defines a whole new optimisation problem to determine the number of charging stations required on the island. The results of this optimisation will not directly affect the main problem, the only effect will be the increasing of the consumption timeseries, by the energy needed for the vehicles charging.

This module's aim is not only to install the charging station needed at the moment of the computation. Instead, it assumes that all the vehicles of the island will be substituted by electrical ones in the future, and the goal is to install the charging points needed to facilitate the electric transition.

For this reason, many different inputs are required to model the transportation demand of the island. Vehicles are divided between inhabitants', tourists', and urban services' vehicles. For each category the number of vehicles present on the island must be provided to the program in the form of timeseries. Moreover, hourly timeseries are needed of the percentages of driving and charging vehicles for each category. These quantities are demanded as a percentage since they should be computed over the possibly few electric vehicles already present on the island.

All these data are not easy for an end user to provide, even an approximation cannot be obtained easily. That is why a study was made on touristic islands' transportation demand and charging profiles, to provide some default values for users who do not have such data at hand (A.P.Robinson, 2013) (Tristan Dodson, 2019) (Energy, 2021) (Levin Skiba, 2018).

Another assumption made by the model is that inhabitants will install their own private recharge stations, and only a small percentage of the vehicles will be using the public ones during the day. The feasibility of installing private recharge stations depends on the island's surface, population, and buildings. As a rough approximation, the percentage of inhabitants using public stations is computed in function of the population density of the island.

Once the transportation patterns are identified, the vehicles' electrical consumption is computed and added to the consumption timeseries of the main problem. Then a new MILP problem is defined, optimising the number of fast and slow charging stations to fulfil the recharge needs while minimising the costs.

The sizing results of this module are added to the same results file used for the main model.

Parameters

General parameters

- $pop(t)$ number of population's vehicle at time t
- $serv(t)$ number of urban services' vehicle at time t
- $tour(t)$ number of tourists' vehicle at time t
- $char_{pop}(t)$ percentage of population vehicles charging at timestep t
- $char_{serv}(t)$ percentage of urban services' vehicles charging at timestep t
- $char_{tour}(t)$ percentage of tourists' vehicles charging at timestep t
- $driv_{pop}(t)$ percentage of population vehicles driving at timestep t
- $driv_{serv}(t)$ percentage of urban services' vehicles driving at timestep t
- $driv_{tour}(t)$ percentage of tourists' vehicles driving at timestep t
- d island's population density
- d_{limit} island's density limit: below this density, no private vehicle will use public chargers
- $E_{vehicle}$ [kWh] maximum capacity of a vehicle's battery
- P_{slow} slow charge max charging power
- P_{fast} fast charge max charging power

Available spaces

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- $S_{inst,slow}$ [m^2] space needed for the installation of one slow charging point
- $S_{inst,fast}$ [m^2] space needed for the installation of one fast charging point
- $S_{EV,tot}$ [m^2] total space available for the installation of EV charging points

State of the current installation

- $Installed_{slow}$ number of already present slow charge charging point
- $Installed_{fast}$ number of already present fast charge charging point

Cost

- $C_{inst,slow}$ [€] installation cost of one slow charging station
- $C_{inst,fast}$ [€] installation cost of one fast charging station
- $C_{O\&M,slow}$ [€/kWh] operation and maintenance cost of one slow charging station
- $C_{O\&M,fast}$ [€/kWh] operation and maintenance cost of one fast charging station

Using the input parameters regarding the population density of the island, we can compute the value α_{pop}, representing the percentage of charging inhabitants' vehicles which are charging in public recharge points. The higher the population density, the more probable it is for a private to have the need to charge in public points. It is defined as follows:

$$\boldsymbol{\alpha_{pop} = \max\left(0, \tan^{-1}\left((d - d_{limit})/d\right)\right)} \quad \text{[Equation 68]}$$

Using this definition, the end user can choose what is the limit below which no private inhabitant will be using public points. Above d_{limit}, the higher the value of d, the closer α_{pop} will be to 1.

Contribution to main model's consumption

As explained previously, this module defines a new independent MILP problem, and the only connection to the main module is the increase of the consumption timeseries, given by the demand of electric vehicles. This demand is computed using the input parameters of this module, the following way:

$$char_{pop}(t) \cdot pop(t) + char_{serv}(t) \cdot serv(t) + char_{tour}(t) \cdot tour(t) \quad \text{[Equation 69]}$$

This quantity is added to the general consumption of the island $L(t)$, for every timestep $t = 1, \dots, T$.

Variables

This module is characterized by two sizing variables and two operational time-dependent variables, all **integers**.

$$\boldsymbol{n_{slow}} \in \mathbb{N} \quad \text{[Equation 70]}$$

Number of slow charging stations to be installed.

$$\boldsymbol{n_{fast}} \in \mathbb{N} \quad \text{[Equation 71]}$$

Number of fast charging stations to be installed.

$$\boldsymbol{A_{slow}(t)} \in \mathbb{N} \quad \text{[Equation 72]}$$

Indicates the number of **active** slow charging stations at each timestep.

$$\boldsymbol{A_{fast}(t)} \in \mathbb{N} \quad \text{[Equation 73]}$$

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Indicates the number of **active** fast charging stations at each timestep.

In total this module adds $2T + 2$ variables to the model, where T is the number of timesteps of the model.

Internal constrains

Spatial constraint installation:

$$\boldsymbol{n_{slow}} \cdot S_{inst,slow} + \boldsymbol{n_{fast}} \cdot S_{inst,fast} \leq S_{EV,tot}$$ [Equation 74]

Current installation constraints:

$$Installed_{slow} \leq n_{slow}$$ [Equation 75]

$$Installed_{fast} \leq n_{fast}$$ [Equation 76]

The following is the core constraint of this module and forces the active stations to always meet the recharge demand.

$$char_{pop}(t) \cdot \alpha_{pop} \cdot pop(t) + char_{serv}(t) \cdot serv(t) + char_{tour}(t) \cdot tour(t) \leq A_{slow}(t) + A_{fast}(t)$$ [Equation 77]

The remaining constraints force the number of stations to be installed to be always equal or higher than the active stations at every timestep.

$$A_{slow}(t) \leq n_{slow} \quad \forall\, t$$ [Equation 78]

$$A_{fast}(t) \leq n_{fast} \quad \forall\, t$$ [Equation 79]

Objective function

The objective function of this problem is a cost function, just like the main problem's objective function.

$$\boldsymbol{F_{obj}\left(n_{slow}, n_{fast}, A_{slow}(t), A_{fast}(t)\right) = C_{inst,slow} \cdot (n_{slow} - Installed_{slow}) + C_{inst,fast} \cdot (n_{fast} - Installed_{fast}) + C_{O\&M,slow} \cdot P_{slow} \sum_t A_{slow}(t) + C_{O\&M,fast} \cdot P_{fast} \sum_t A_{fast}(t)}$$ [Equation 80]

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3.5 Full energy balance and full objective function

The energy balance are the core constraints of the model and, alongside with the objective function, are the only point of contact of the various modules.

Every module, if activated, contributes in a different way to the energy balance, increasing either generation or consumption. All the contributions of each module are specified in the module's section. For clarity, we report here the formulation of the energy balance constraint at a generic timestep t, with all the modules activated.

$$\begin{gathered} L(t) = P_0 \cdot \frac{H(t)}{G_{ref}} [1 + \gamma(T_m - T_{ref})](1-d)^n + \\ P_{max,onshore} \cdot c_{onshore} \cdot w_{s,onshore}(t) + \\ P_{max,floating} \cdot c_{onfloating} \cdot w_{s,floating}(t) + \\ P_{max,foundation} \cdot c_{onfoundation} \cdot w_{s,foundation}(t) + \\ P_{oper,battery}(t) + \\ P^-_{oper,H2}(t) - P^+_{oper,H2}(t) + \\ P_{existing\ intercon,oper}(t) + P_{new\ intercon,oper}(t) + \\ P_{0pros} \cdot \frac{H(t)}{G_{ref,pros}} [1 + \gamma_{pros}(T_{m,pros} - T_{ref,pros})](1 - \\ d_{pros})^{n_{pros}} + P_{oper,pros}(t) \end{gathered} \qquad \text{[Equation 81]}$$

Where $L(t)$ is the consumption of the island at timestep t. Note that $L(t)$ is not necessarily the data provided by the user in the consumption timeseries, but it might have gone through the following transformation:

a. Increase of a percentage provided by the user, to oversize the results of the optimisation.

$$L(t) = (1 + \alpha_{oversize}) \cdot L(t)$$

Note: the formula above is not an equation, it is an assignation of value, i.e. the updating of the value of $L(t)$.

b. If the mobility module is activated, the consumption is increased by the amount of electric consumption that will be needed after the electric transition of vehicles.

$$L(t) = L(t) + char_{pop}(t) \cdot pop(t) + char_{serv}(t) \cdot serv(t) + char_{tour}(t) \cdot tour(t)$$

Once again, this formula is an update of the value $L(t)$.

We also report here, for the sake of completeness, the general form of the objective function.

$$\sum_{modules} c_{inst} \cdot P + \sum_{modules} \left(c_{O\&M} \cdot \sum_{t=1}^{T} E(t)\right) \qquad \text{[Equation 82]}$$

In this equation, P is the sizing variable of the module, and $E(t)$ is the energy flowing through the module at time t. In the case of generation modules, $E(t)$ is the generated energy, whereas in storage modules it is the operational variable (multiplied by HxT the hours per timestep).

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In the case of the interconnection modules, $E(t)$ is the energy bought from the island, while $c_{O\&M}$ is the cost of the energy.

4 OPTIMIZATION APPROACH

4.1 Model complexity: process

After the addition of the latest modules, which were not present in the D.1.2 formulation (prosumers and EV in particular), the model had reached a level of complexity which made it impossible to solve for long timeseries (usually more than a month). Ideally the model should consider one year of data (consumption and generation), in order to let the seasonal behaviour develop. For instance, one of the use cases of the hydrogen based storage system is a yearly cycle of charge/discharge. Clearly the solver cannot find such solution if applied to one-month-long models. To solve this problem different approaches were considered, from a global model reformulation to line-to-line optimization. Such measures will be described here below.

4.1.1 Hours grouping

Usually in this type of models a balance between precision and complexity needs to be found. One way to reduce the precision, and hence the complexity, is to lower the granularity. Instead of having one-hour timesteps, the parameter HxT (hours per timestep) was added to the model (default value $= 1$). By setting this parameter to a value n higher than 1, one timestep will consist of n hours. This change affected the whole formulation of the model, in particular the conversion from power to energy and vice-versa, which is needed in almost all of the modules.
Trading off precision for computation time by grouping hours clearly has downsides. Not only the lower precision in the timeseries, but also the risk of compromising the generations module. The generation is in fact, based on weather condition timeseries (solar irradiance, temperature, and wind speed), which are more sensible to hours grouping than power timeseries. That is, for instance, during winter days for PV generation: if peak solar irradiance hours are grouped together with low irradiance hours, the choice of installing such generation system might be seriously affected. For this reason, hours are grouped after calculating the generation, so that all the timeseries on which the grouping is performed are power (or energy) timeseries.
This implies that the timeseries given to the model should always have a one-hour granularity, regardless of the HxT parameter.

4.1.2 Float instead of integer variables

Integer (and boolean) variables take a noticeable toll on the solver's speed, by significantly raising the complexity. For this reason, they were replaced by integer variables unless it was strictly necessary for them to be integers.
Specifically, the sizing variables of wind and solar energy generation system were initially of integer type. The change to floating type affected all the modules that include some type of generation (wind onshore, offshore floating and offshore with foundation, solar park and solar prosumers). Instead of having a variable representing the size of the installation in solar panels or windmills, it represents the size of the global installation in kWp (peak kW).

The main downside of this change is, as usual, a loss of precision in the computation.

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Specifically, the solver cannot handle non-linear operators such as floor or ceiling, hence every time the integer variable is needed in the model, it cannot be computed exactly.
For example, solar installation prices are given per panel, hence in the objective function this value should be multiplied by the sizing variable divided by the peak power of a single panel,

$$C_{inst,PV} \cdot \left\lceil {P_0}/{P_p} \right\rceil$$

As mentioned, it is not possible to use the ceiling operator, and that is why the cost is required per peak kW instead of per panel. However this only moves the problem, and does not solve it, since a fraction of a panel cannot be installed.

4.1.3 Boolean variables

Boolean variables have proven to increase the complexity of the computation considerably. When using time-dependent Boolean variables we recorded an exponential computational time (with respect to the number of timesteps used).

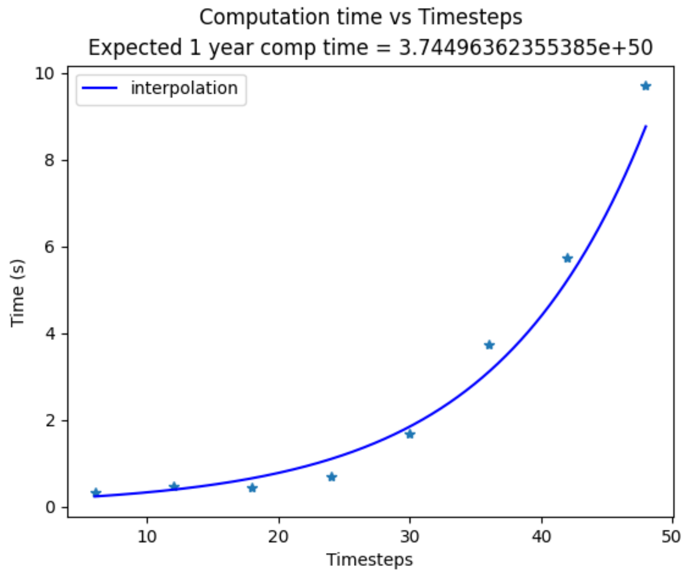

Figure 10: Exponential interpolation of computational time. Active modules: PV park, onshore wind, hydrogen storage, prosumers (old Boolean version). Computational time for 1-year timeseries (11690 variables, 2920 of which boolean) was predicted to be $3 \cdot e^{50}$.

It became evident that full year computations were completely unfeasible. Without the boolean variables however, the exponential approximation was overestimating the computational time and solutions for the full year computation are obtained in matters of hours.

All time-dependent boolean variables have been then removed from the model. The consequence was the loss of all the flexibility provided by this type of variables, which allowed the modelling of piecewise linear functions, such as a maximum between two linear functions.

Specifically, boolean variables were used every time a real variable needed to be multiplied by a different coefficient depending on the sign of the variable itself. The clearest example is the battery operational variable, which is representing the energy flow in and out of the Li-ion batteries. In the first formulation of the problem, these variables are multiplied by an efficiency coefficient, modelling the energy loss due to the battery functioning. The efficiency, however, is different depending on the sign of the variable:

- if the variable is positive, the batteries are charging, and the coefficient is lower than 1
- if the variable is negative, the batteries are discharging, and the coefficient is higher

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than 1

This was achieved by modelling auxiliary variables (through the boolean variables), representing the positive part of the operational variable, i.e.:

$$auxiliary(t) = \max(0, operational(t)) \quad \forall t$$

This kind of mathematical artifice was used not only in the batteries, but also in the prosumers and interconnection modules.

In the final version of the model all these constructions were eliminated. In the batteries and prosumers modules the efficiency value is the same for charging and discharging (default is set to 1), resulting in a loss of precision in modelling the island energy systems.

These small inaccuracies in the approximations, however, can be accounted for by oversizing the system before and/or after the computation. To oversize it before the computation, an input parameter was added, representing a percentage that will be summed to the consumption timeseries. By increasing the consumption, the solutions will satisfy a request higher than the island's, effectively oversizing the system.

On the other hand, as mentioned in the introduction of this document, the solutions of the model should be used as a baseline and a first approximation by an expert. The end user should look at the results of the computation as one of the sources of information they have at their disposal to decide the final sizing of the installations. Hence after the computations the solutions will go under another phase of evaluation and, possibly, changes.

4.2 Solver selection and hardware specifics

The model has gone through numerous changes during its development, and the solver selection was no exception. The library used to code the model, pyomo, is compatible with many different solvers, free and paid. Initially we used a variety of free solvers, eventually settling for cbc, by COIN-OR. Cbc is the solver we recommend to any user who does not have access to commercial solvers.

During the phase of enhancing performances to obtain the solutions of a one-year computation in a feasible time, the purchase of a professional solver was evaluated. Eventually it was decided to use CPLEX by IBM, which is the solver used to obtain the results described in the next chapter.

It was observed that CPLEX consistently keeps the computational time below half of cbc's time when no boolean variables are involved in the model, but usually it lowers the time to one third. When boolean variables are needed however, the difference of computational performance reaches the whole order of magnitude (Templ, 2012).

Regarding the hardware specifics, the model was run on a single server with 32 CPUs, not all of which were always available. CPLEX has the built-in functionality of dynamically changing the number of cores it is taking to solve the problem, which allows to not fix a number of CPUs to dedicate to the model, although this option is available.

We want to reiterate that the flexibility and adaptability of the model makes it feasible for anyone to choose their own set of parameters, including the solver used, to reach their own conclusion. If a free solver had to be used, for instance, a trade-off between number of activated modules and number of timesteps could be done, to reach a point of complexity which enables the solver to find the solution in a reasonable time. The lowering of the number of timesteps could then be achieved in different ways: by increasing HxT (the hours per timestep parameter), if a high level of granularity is not required, or by decreasing the length of the timeseries, if seasonality does not play a big role in the problem.

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5 OPTIMIZATION PERFORMANCE: RESULTS

5.1 Particular case: Borkum

Specific parameters and data were collected from the Borkum island, to run the model adjusted to Borkum's situation. In particular, the whole island consumption timeseries from 2019 and meteorological conditions such as wind speed and irradiance were used in all the runs of the model.

In all of the following simulations, an **oversizing** parameter of 10% was applied to the consumption timeseries.

The parameters used for these simulations are reported in 7

First, let us present the sizing results when all the modules are activated:

- Objective function value: 967837 €
- EV objective function value: 249500 €
- **Number of EV slow charging points**: 501
- **Number of EV fast charging points**: 1
- **Number of wind turbines**: 0
- **Number of solar park panels**: 0
- **Number of prosumers panels**: 0
- **Prosumers batteries size**: 0 kWh
- **Batteries size**: 500 kWh
- **Hydrogen tank size**: 0 Kg

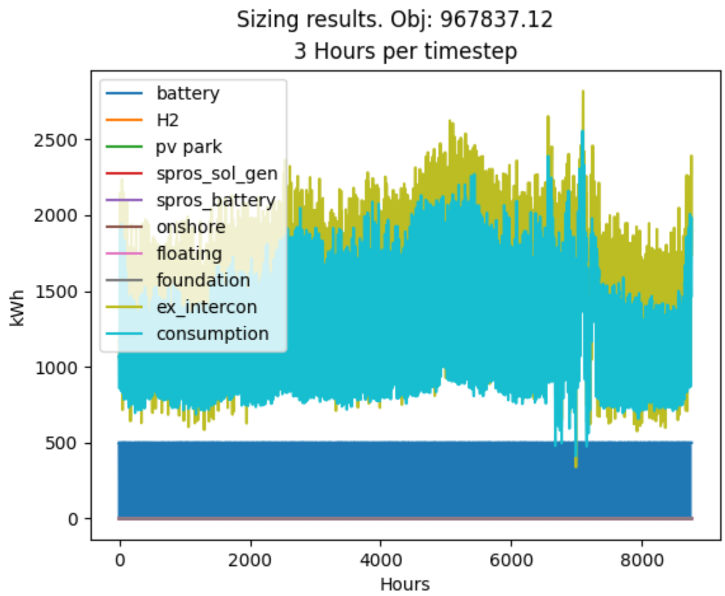

Figure 11: Global sizing results of the run with all modules activated. Number of timesteps 2920, hours per timestep 3.

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This run counts 2920 timesteps, each of which has a duration of 3 hours.

The battery size did not raise more than its initial charge (500 kWh) that we gave as a parameter, which is half the charge of the planned installation.

The most efficient technology in this case is clearly the interconnection, which is used to satisfy the island's energy need at every timestep, with the aid of a battery installation. The interconnection is never used to send energy to the mainland, since it never goes below 0. The energy in excess is stored in the battery, which is emptied as soon as it reaches the SOC of 500 kWh.

Even though this is the mathematically most efficient and cheapest result, it clearly does not provide the information we need. We will address this later, let us focus on the EV module results.

The solver suggests the installation of 502 charging points, which is also an unfeasible result. It is because tourists are considered all to have an electric car and to be driving around the island. However, we know this is not really the case in Borkum since tourists are likely to only use their vehicle to get to the island on a ferry.

In fact, if we remove the tourists from the model, the result is the following:

- Objective function value: 962143 €
- EV objective function value: 4500 €
- **Number of EV slow charging points**: 11
- **Number of EV fast charging points**: 1
- **Number of wind turbines**: 0
- **Number of solar park panels**: 0
- **Number of prosumers panels**: 0
- **Prosumers batteries size**: 0 kWh
- **Batteries size**: 500 kWh
- **Hydrogen tank size**: 0 Kg

The charging points required now are 11, a number consistent with the initial assumptions. In this case the operational results are the same, meaning that the interconnection was the only technology used, alongside the batteries. Note that the value of the objective function has lowered, because the consumption timeseries in the second case does not include the consumption of the tourists' electric vehicles.

Let us now address the generation technology results. Since the interconnection cable is already installed in Borkum, buying the energy from the mainland is the most cost-efficient way to satisfy the island's consumption. However, accelerating energetic independency is one of the goals of the project, which means this is an unacceptable result. One solution could be to increase the energy cost in the interconnection parameters, in order to penalise the decision to import energy through the cable. However, the fact that there are no cable installation costs, makes this technology so efficient that it is hard to set a reasonable penalisation cost. By running multiple tests it is clear that the solver keeps using the interconnection until its cost is increased by a factor of at least 10^2. The fact that the penalization factor is at least two order of magnitudes greater than the actual cost, makes the results obtained by such runs meaningless.

For this reason, we chose to portrait an ideal scenario, where the interconnection is not used at all. In this case, for better precision, the number of timesteps used was 4380, meaning each timestep consists of two hours.

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- Objective function value: 111150127 €
- EV objective function value: 4500 €
- **Number of EV slow charging points**: 11
- **Number of EV fast charging points**: 1
- **Number of onshore wind turbines**: 7
- **Number of offshore floating wind turbines**: 0
- **Number of offshore wind turbines with foundation**: 0
- **Number of solar park panels**: 185668
- **Number of prosumers panels**: 0
- **Prosumers batteries size**: 0 kWh
- **Batteries size**: 178433 kWh
- **Hydrogen tank size**: 80 Kg

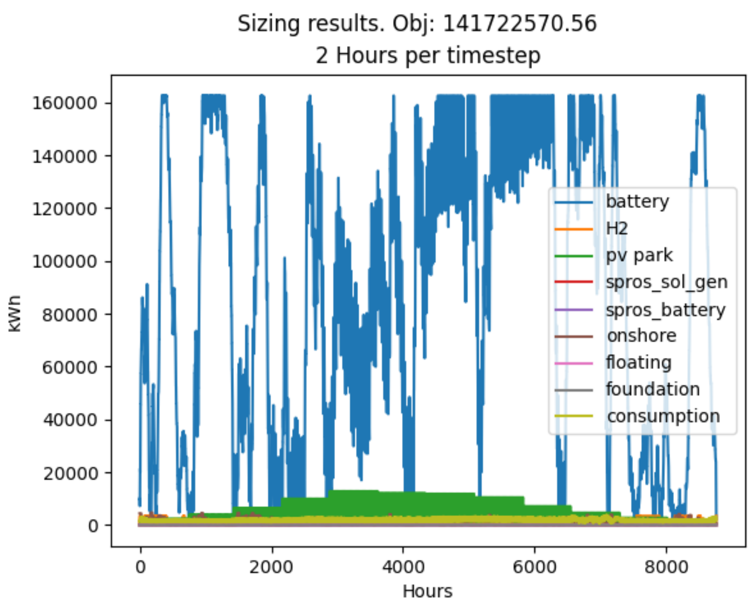

Figure 12: Global operational results of the run without interconnection. Number of timesteps 4380, hours per timestep 2.

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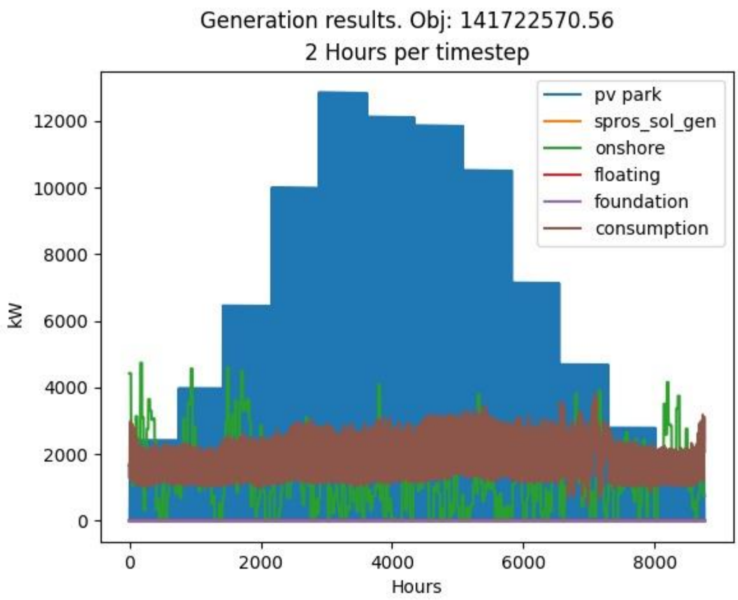

Figure 13: Generation results of the run without interconnection. Number of timesteps 4380, hours per timestep 2.

As anticipated, these are ideal results, but clearly not feasible to be installed on the island in the duration of the ISLANDER project. The objective function value, which is the sum of all installation and maintenance costs, is higher than a hundred millions Euros, an investment not in the possibilities of the project. However, some interesting conclusions can be drawn.

For instance, the fact that both wind and solar technology was installed means that the solver did not just find the most cost-efficient generation technology and minimized the installation. The right mix of both technologies provides the most effective form of renewable generation.

The same can be said about the storage: both lithium batteries and the hydrogen-based storage system were installed. This implies that the optimization process was able to bring out the best side of each technology, even if the H2 storage system was not employed for a seasonal charge.

The rooftop installation was discarded by the solver, mainly because it is outperformed by the PV park plus Li-ion batteries combination.

Unfortunately, due to geographical problems arisen on the island, no windmill can be installed, and the two already present will be dismantled. Let us run a simulation in which only the solar generation systems (PV park and prosumers) are activated.

For this run, we rise the value of the initial charge of the batteries to 10 MW, since there is no generation at night and the system needs a higher initial energy to work with.

- Objective function value: 272175262 €
- EV objective function value: 4500 €
- **Number of EV slow charging points**: 11
- **Number of EV fast charging points**: 1
- **Number of solar park panels**: 1140186
- **Number of prosumers panels**: 0
- **Prosumers batteries size**: 0 kWh
- **Batteries size**: 106279 kWh

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- **Hydrogen tank size**: 423 Kg

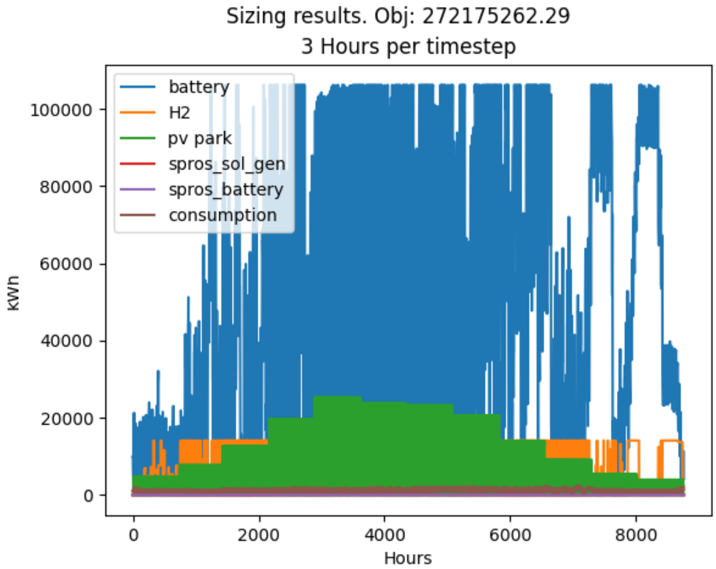

Figure 14: Global sizing results of the run with solar generation only. Number of timesteps 2920, hours per timestep 3.

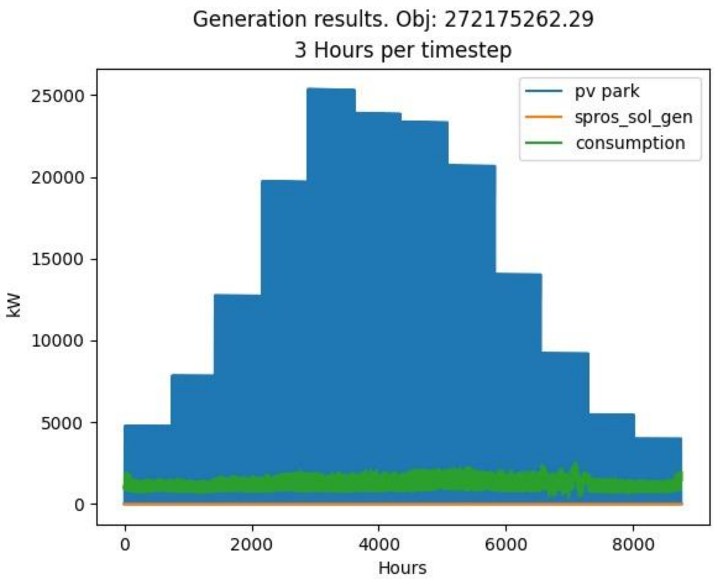

Figure 15: Generation results of the run with solar generation only. Number of timesteps 2920, hours per timestep 3.

In this scenario the global costs have risen to more than a quarter billion Euros, and the installation counts more than a million solar panels. The space restrictions were not considered in this simulation, because they would have made the problem unfeasible (i.e. there would be no possible solution). As expected, this is not really viable, also due to the climate in Borkum, which suits more wind installations than solar panels.

In this scenario as well the optimal solution does not include prosumers' installations, but a mix of Li-ion batteries and hydrogen as storage solutions.

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5.2 Particular case: Follower islands

Task 1.6 will be in charge of including replication strategy. In this deliverable an initial approach for Borkum was presented, but the model will be readjusted for the rest replication in T1.6.

The task of recollecting all the data from the follower islands is still ongoing, and it has not reached a level that allows a full simulation on an island different from Borkum.

Once the year-long consumption timeseries of the follower island is obtained, alongside all the rest of the parameters, the model will be a powerful tool to perform early simulations in different scenarios and draw some early conclusions. It can be used on a global scale to optimise the whole island's installations, or to compare two different installations of the same module, with different specifics.

6 MAIN CONCLUSIONS

As anticipated in the introduction, the optimisation tool that was developed is quite complex and works on a high level, trying to represent and simulate the situation of the whole island as best as possible. This implies that the level of detail of the single modules or systems cannot be very high, due to various reasons. The main one is computational complexity, which forces us to find a balance between number of modules and the complexity and quantity of details of said modules.

Being the scope of Task 1.3 to optimise all the DER and HES of the island as an energy hub, it was mandatory to include all the possible systems in the tool. Moreover, since the optimisation tool must not be specific for Borkum, the more modules are included, the greater it is its flexibility and ability to adapt to a new scenario.

For these reasons, alongside the fact that there are no non-renewable energy modules in the tool, the results obtained do not really refine the initial layout. They rather paint an ideal scenario, in which the island does not rely on any fossil fuel energy and show the very high amount of renewable sources needed to achieve that. The issue with the installation of windmills, which are arguably the most efficient renewable energy source in Borkum, only leaves the solar energy as an option, forcing the solver to cover more than a third of the island with solar panels, which is clearly out of the scopes of the project.

Unfortunately, it is not possible to create a flexible modular program which model the behaviour of a whole island's DER & HES and obtains results which refine the initial sizing of the installation. The goal of the project is to make a step towards decarbonisation and autonomy of the Borkum island, and the results of the optimisation confirm that to reach the full objective, further work and investments need to be done after the end of the project.

The optimisation tool however has proven to work well by giving consistent results in different scenarios and can be a very effective first approach to layout the initial sizing of the installations. The possibility to know beforehand what is the approximate investment that needs to be done to completely decarbonise an island (or an isolated energy hub), can be very helpful in the initial stages of a project.
We believe this optimisation tool will prove even more useful for the follower islands, on which it can be used before the beginning of the installation to study various scenarios beforehand. The fundamental condition to use the program in the most effective way is to provide the parameters as accurately as possible, to exactly recreate the conditions on the island. Once the parameter recollection is completed, this program becomes a powerful tool to avoid mistakes and to go in the right direction since the very beginning of a project.

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7 ANNEX A: PARAMETERS

We report here the parameters that have been used for the Borkum's simulations presented in 5.1.
These parameters are the result of a recollection work done by AYE, NBG, IDE, ZIG and CEG. Some of the parameters (e.g. installation or maintenance costs) could not be retrieved for Borkum's specific case. A work of studying and collecting general data by taking an average has compensated this lack of data (Luca Massidda, 2017) (Andy Walker, 2020) (Alberto Ghigo, 2020) (Rosenauer, 2014)
This is a typical configuration file of the model, specifically the one that has been used for the optimal design of the installations without the interconnection.

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