OSMOSE

OPTIMAL SYSTEM-MIX OF FLEXIBILITY SOLUTIONS FOR EUROPEAN ELECTRICITY

Methodology report for application-specific design of Battery Energy Storage System

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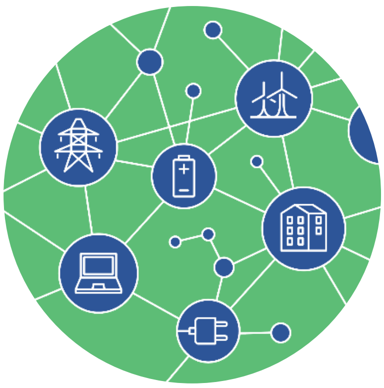

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List of acronyms and abbreviations

In the table is listed the acronyms and abbreviations used in this document.

Acronym	Meaning
AC	Alternative Current
BA	Bat Algorithm
BESS	Battery Energy Storage System
CAPEX	Capital Expenditure
DC	Direct Current
DE	Differential Evolution
DG	Distributed Generations
DOD	Depth of Discharge
DP	Dynamic Programming
ESS	Energy Storage System
GA	Genetic Algorithm
GAMS	General Algebraic Modelling System
GHI	Global Horizontal Irradiation
HESS	Hybrid Energy Storage System
HRES	Hybrid Renewable Energy System
IRR	Internal Rate of Return
LCC	Life Cycle Cost
LCOE	Levelized Cost of Energy
LOLE	Loss of Load Expectation
NPV	Net Present Value
OCV	Open Circuit Voltage
O&M	Operation and Maintenance
OPEX	Operational Expenditure
PSO	Particle Swarm Optimisation
PV	Photovoltaic
RE	Renewable Energy
RES	Renewable Energy System
SOC	State of Charge
SOE	State of Energy
SOH	State of Health
SPIDER	Simulation Platform for the Integration of Distributed Energy Resources
WACC	Weighted Average Cost of Capital

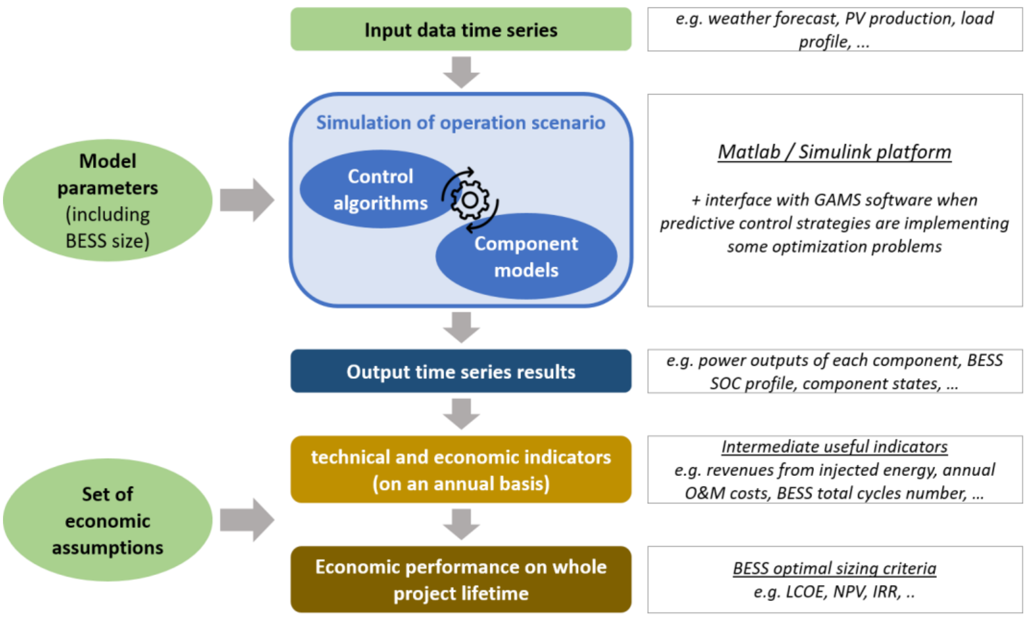
0 Executive summary

This deliverable is related to the work performed in the sub-task 7.3.1 "Optimized application-specific design of BESS" of the OSMOSE project. This task aims to develop methods and associated tools to optimize the design of BESS by taking into account both the application and the storage performance over its lifetime.

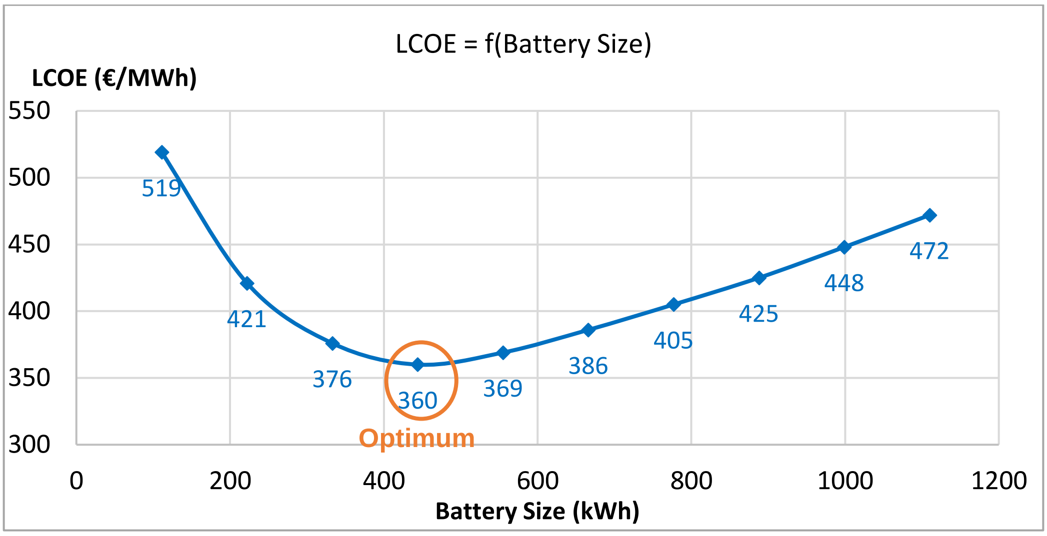
The document is organized as follows:

- Section 1 introduces the overall challenge of BESS optimal sizing and describes the objectives of the present study.
- Section 2 focuses on the state of the art on battery optimal sizing, by providing a comprehensive review of battery sizing criteria, methods and its applications in various renewable energy systems.
- Section 3 describes the simulation-based analytical method which has been developed for BESS optimal sizing in the context of the study. It also defines the scope of the sensitivity analysis which has been carried out to identify the most influencing factors to consider during a BESS sizing procedure.
- Section 4 explains how the methodology has been implemented for two different illustrative BESS application cases, which were then used for the sensitivity analysis purposes.
- Section 5 details the comparison results obtained for each of the influencing factor investigated through the sensitivity study.
- Finally, the conclusions of the study are given in section 6, which provides a synthesis of the different results and explains how to take advantage of them in the design phase of BESS projects.

The simulation-based method for optimal sizing developed within this study and implemented on the two illustrative application cases is represented on the following figure.



An example of sizing results obtained through this method is illustrated on the next figure, where the chosen indicator is the levelized cost of energy (LCOE). On this graphic, minimal LCOE value (360€/MWh) is obtained with the battery nominal capacity of 440 kWh, which is the BESS optimal size in this case of figure.



By using two very different illustrative BESS use cases, the study enabled to:

- Illustrate how the generic simulation-based methodology developed and implemented for the study purposes can be applied to different use cases, for systems composed of various energy components and/or different energy application purposes,
- Distinguish, among the influencing factors investigated through sensitivity analysis, those whose impact has the same magnitude regardless to the application from those whose impact is application-dependent.

The conclusions of the sensitivity analysis for each of the investigated factors are summarized in the following table:

Factor	Conclusions
Precision of the BESS efficiency behaviour	A variable efficiency behaviour can be **approximated by an average efficiency** single value **without any impact on optimal sizing**. However, **the average efficiency value must be set precisely** since the sizing indicator value is strongly affected by this parameter. An error on BESS efficiency value causes an error bordering on the same magnitude on the sizing indicator.
Degradation of battery capacity due to ageing	**Ageing must be taken into account in optimal sizing**. In case of limited availability to precise ageing parameters, an estimation of average degradation is sufficient to obtain appropriate confidence levels on sizing indicators.

Factor	Conclusions
Degree of technical modelling of the BESS component	**Optimal sizing does not require a high degree of technical modelling**: a simplified model of BESS directly handling power and energy quantities from global efficiency parameters is adapted and leads to the same sizing indicator values, within a one percent interval, as an in-depth performances model based on equivalent-circuit equations.
Simulation time-step	The influence of the simulation time-step on optimal sizing **strongly depends on the application time constants** related to the events impacting the operation costs or incomes. An hourly time-step should in general not be recommended as it could lead to an important loss of information about these events. When such events are related to PV fluctuation or fuel generator operation, like on the 2 illustrative cases, a time-step of 10mn seems suitable.
Degree of complexity of control algorithms	**Strong impact**: different control strategies may lead to a different optimal BESS size, as illustrated with the hybrid microgrid application. It is therefore recommended to clearly define the control strategy before determining the optimal size.
Forecast quality when predictive control is facing forecast errors	**Highly depends on the application purpose:** if the main function of BESS is to compensate for forecasting errors in the RE sources, as for illustrative application #1, forecast quality is of the highest importance for optimal sizing: a 50% improvement of the forecast quality induced a difference of 15% of the sizing indicator value for application #1.

At the stage of modelling or collecting data for optimal sizing purpose, these conclusions should help to:

- Concentrate the effort on the crucial factors which have the strongest influence on the optimal size determination.
- Identify where relevant approximations can be applied in the calculation to save some unnecessary efforts and computation time without degrading the accuracy of the result.

1 Introduction and objectives

Due to the number and variety of services they can provide, energy storage is likely to play a significant role in the optimal mix of flexibility solutions for the European power system.

Of the various type of ESS technology available, battery energy storage systems (BESS) have attracted considerable attention with clear advantages like fast response, controllability, and geographical independence [1, 2]. Besides the advantages mentioned, BESS also have a wide scope of applications ranging from short-time power quality enhancement to long-term energy management, as well as reliability enhancement, uninterrupted power supply and transmission upgrade deferral.

BESS can consequently deliver multiple benefits that will enhance grid performance, operability and security together with reducing energy production and delivery costs. The many functions of this powerful tool include its ability to:

- Offset additional need for peak generating capacity,
- Enhance optimal operation of existing generation facilities,
- Integrate intermittent renewable energy technologies,
- Provide ancillary services such as load following, area regulation and spinning reserve,
- Reduce transmission congestion,
- Defer transmission and distribution upgrades and provide an alternative to inflexible lumpy transmission and distribution capacity additions,
- Support and enhance demand response resources.

BESS thus mitigate some of the current and future challenges that grid operators face to improve the overall economics of the infrastructure while reducing the overall carbon footprint and providing reliable services. Specifically, the challenges include managing peak demand, resolving transmission line congestion, and integrating renewable energy technology in a climate of financial risk adversity that will limit new transmission construction.

Over the last decades, significant research and development has been conducted to improve cost and reliability of battery energy storage systems. Although certain battery storage technologies may be mature and reliable from a technological perspective [2], with further cost reductions expected [3], the economic concern of battery systems is still a major barrier to be overcome before BESS can be fully utilised as a mainstream storage solution in the energy sector. The investment costs for deploying a BESS can be significant. That is the reason why, during the implementation of battery energy storage systems, one of the most crucial issues is to optimally determine the size of the battery to define the appropriate balance between the technical improvements brought by the battery and the additional overall cost.

In other words, the trade-off between using BESS to improve energy system performance and to achieve profitable investment is a critical decision to make for project developers. In this regard, the optimisation of BESS sizing is a vital issue to balance this trade-off, by attaining the best solution for multiple, or even contradictive, requirements.

Determining the optimal BESS size for a specific application is a complex task because it directly or indirectly depends on a lot of factors, parameters and uncertainties such as:

- Application control strategy, which will determines how the storage system will be used for the considered application,
- Energy and power application needs over the project lifetime,
- Application technical constraints, such as AC transmission or distribution grid requirements in terms of OVRT, availability and/or redundancy requirements,
- Battery technologies and characteristics, such as efficiency,
- Degradation of the performances of the battery over its lifetime (capacity and/or power degradation due to battery ageing),
- Uncertainties related to renewable energy sources / forecast errors / load demands / energy prices,
- Realistic economical assessments to correctly evaluate investment as well as operation costs throughout the project lifetime.

This report describes a generic method which has been developed to determine the optimal size of a BESS involved in a specific power application. In order to provide a better understanding of the influence of the different factors listed above, this method has been used to carry out several sensitivity analyses aiming at assessing their degree of impact on the BESS optimal size determination.

By highlighting the main factors which have the most significant impact on the optimal sizing results, the goal is to provide useful information for real projects specification phase, enabling to distinguish crucial factors which have the strongest influence on the BESS sizing from those having a minimal impact and which can be neglected or approximated if their exact knowledge is not available at the time of the design stage.

2 General approach for BESS sizing

2.1 BESS sizing criteria

There are a range of performance indicators for determining the size of BESS, which can be used either individually or combined to optimise the system. BESS sizing criteria can be divided into three classifications: financial, technical and hybrid criteria [4].

2.1.1 Financial indicators

One key driver for determining the size of a BESS is the financial return for the operation of the system. A key attraction of financial indicators is that there is a common unit for making decisions, namely the local currency, enabling the comparison of different alternatives. Even with the benefit of a common unit for comparison, there are several different indicators that can be used as optimisable parameters for designs. Many studies have **looked at the overall costs and benefits of the battery system** in RES over the operational lifetime of the system. These approaches used the time value of money, via a discount rate, to determine overall costs on a lifetime basis, including levelised upfront capital costs, annual/daily operation and maintenance (O&M) costs, as well as fuel costs if the corresponding generators were applied. The indicator to be optimised can then be the Net Present Value (NPV) of the system [5], which should be maximised, or the levelised cost of electricity (LCOE) on an annual basis [6] or daily basis [7, 8], which should be minimised. The NPV in [5] was formulated as the difference of levelised daily operation costs with and without ESS, whereas the LCOE in [6] took the annualised investment cost, annual operation cost and fuel cost into account directly. During the formulation, the modelling of a BESS's cost is a key issue. Therefore, it is worthwhile to mention the study of [9], where a detailed explanation of the methodology for calculating and analysing a BESS's total cost and annualised life cycle cost (LCC) can be found. However, the modelling of BESS costs in most studies associated with BESS sizing used neither the total cost nor LCC. They generally included the capital cost of BESS, which was then converted into an annual/daily cost by taking into account the interest rate [10], and the annual/daily O&M cost of BESS. The replacement cost of BESS was included in the formulations in [5] and [6], but the disposal and recycling costs of BESS were rarely considered.

Another financial indicator approach is **to look at maximising the market benefit of the inclusion of a battery system** in a RES. One significant case is microgrids, where the total benefits in grid-connected mode are maximised and the total costs associated with being in islanded mode are minimised [11, 12]. The total costs of microgrids include the levelised operating costs from BESS and other running components, whereas the total benefits were calculated through the difference between the benefits from selling electricity and the total operating costs. More details about these formulations can be found in [11, 12]. Other examples looked at partial financial values, rather than the total costs/benefits, for instance, maximising the difference between the sale of electricity to the grid and purchase from the grid for a grid-connected system [13].

2.1.2 Technical indicators

As opposed to financial indicators, technical indicators do not have a common unit and so direct comparisons in different cases with a number of technical criteria can be difficult. Consequently, popular ways to integrate the technical indicators is to achieve a single optimisation goal or to include them as constraints during the sizing process. In the optimisation, technical indicators can be quantified by binary variables, i.e. do they meet (or not meet) the requirements, or as a specific value goal, such as renewable curtailment and forecast errors which can be minimised. When considering technical indicators for battery inclusion in renewable systems, it is worth noting that they all serve to quantify the support of the BESS for the dynamic or steady state characteristics of the RES.

To improve the dynamic characteristics (with time horizons less than 1 min), two main technical criteria for both autonomous systems and grid-connected systems are frequency regulation and voltage stability. Both of these indicators can be regarded as binary variables, in other words, to dispatch the battery to meet the frequency and voltage requirements.

Other than dynamic enhancements, a number of criteria concerning steady-state operation (with time horizons greater than 1 min) are also actively applied for BESS sizing, such as reliability [14] and renewable energy curtailment [15]. Curtailment is defined as a deliberate decrease in renewable energy power output to avoid overgeneration, transmission congestions or the risk of instability in the grid. Renewable energy curtailment can be readily quantified as a dumped power profile, i.e. the difference between the dispatched power and the potentially produced power given available resources (wind and sunlight) [16], or accumulated dumped energy, which can be quantified as kWh by integrating the dumped power with respect to time. Thus, curtailment has been adopted as a technical indicator for BESS sizing. Another important technical aspect of dispatching a battery is to improve the features of the power profiles such as peak shaving, constant power output and smoothing of variability. An example of using peak shaving as a sizing indicator is to determine the capacity by regulating the ESS to achieve the daily mean wind power equals to the daily mean load [17]. Another extreme example is to size the battery by delivering a constant power generation for a wind farm [18]. Furthermore, the variability of renewable energy can be smoothed by dispatching the ESS as a low-pass filter, therefore, the size of the ESS can be determined through the behaviours of the ESS [19, 20]. Indicators related to reliability are more commonly adopted for standalone RES, or microgrids operating in islanded mode, to replace limited or expensive backup options. An example of considering reliability in a microgrid is to use the Loss of Load Expectation (LOLE) as the assessment, defined as the expected fraction of unserved load in the microgrid during the simulation period, and 0.1 days/year was defined as the target for the reliability of power supply [21]. Another important approach for determining battery size is to consider the BESS operating to compensate for forecasting errors in the RE sources [22, 23]. This is an important application, especially when the renewable generators are registered to participate in the electricity market dispatch, since excess generation would be required. Therefore, using battery systems to compensate for forecasting errors can improve the utilisation of renewable energy and avoid any potential penalties for non-delivery of bid power/energy. It is worthwhile mentioning that battery cycle life and operational parameters such as Depth of Discharge (DOD), and charge/discharge rates can also be regarded as significant indicators for battery size determination, more often serving as a constraint during the sizing process. There are many ways to evaluate the degradation of BESS. Dragicevic et al. [24] counted the number of cycles over the time horizon for the assessment of battery degradation. Alternatively, State of Health (SOH) can be used to identify the degradation degree of the battery [25], accounting for the ageing from cycling as well as the calendrical ageing [26]. The key battery system parameters and cycle life are technology dependent and system characteristics need to be considered when adopting BESS.

2.1.3 Hybrid indicators

In more recent studies there has been a growing emphasis on considering both financial and technical indicators simultaneously with regards to battery sizing. There have been two major approaches to combine these indicators; the first of these has been mentioned previously, where **technical indicators act as constraints within which the financial indicators** need to be optimised. A good example of this type of approach was given by Bahramirad et al. [21], where the size of the ESS was determined by minimising the investment and operating cost under the restriction of guaranteed reliability. The other major approach is **multi-objective optimisation for hybrid indicators** that consist of both financial and technical metrics. A good example of this type of approach is outlined by Korpaas et al. [27], where the exchange power was smoothed whilst maximising the benefits of the wind farm. We can also imagine a mix between financial performance and environmental indicators, such as minimizing CO2 emissions due to application operation, or to the manufacturing and recycling processes of the chosen battery technology.

In summary, it can be seen that there are a number of criteria that may be selected to allow the determination of BESS size from either a technical or financial perspective. It should also be noted that the critical functions of BESS change with different criteria being used in size determination. A specific example of this is when technical indicators are selected to improve the dynamic characteristics of an energy system, the power capacity of a BESS plays a far more critical role than the total energy capacity. In other words, how rapidly the BESS can deliver power is more important than the overall energy it can deliver. This aspect has manifested itself in studies such as Nazaripouya et al. [28], where battery sizing was found in terms of per unit multiplied voltage regulation duration and for the case of frequency regulation [29]. Generally speaking, the energy and power capacities are both equally important, particularly when looking at multiple technical indicators, but as highlighted by these cases there are specific functions of a BESS where this ceases to be the case. A further way to make the energy capacity (and by extension the physical size of the BESS) a less critical component is the **use of advanced dispatch strategies to achieve multiple functions**, allowing an existing BESS to be used more effectively and for system design to more effectively use the energy and power capacity of a BESS.

2.2 BESS sizing methods

The sizing of battery storage systems can be determined using a wide variety of techniques, with each approach having its own strengths and weaknesses [4]. The complexity of the techniques employed also varies considerably, with approaches spanning simple probabilistic techniques through to mathematical optimisation strategies and nature inspired methods. The focus in this section is on the most common techniques encountered in the literature. The techniques described and discussed are: probabilistic methods, analytical methods, directed search-based methods and hybrid methods.

2.2.1 Probabilistic methods

Probabilistic methods are perhaps the most intuitively appealing and simplest approaches to battery sizing. A flowchart explaining probabilistic methods can be found in Figure 1. The key concept is to use the stochastic nature of the renewable resources, typically solar or wind, to optimise the battery size for the selected criteria.

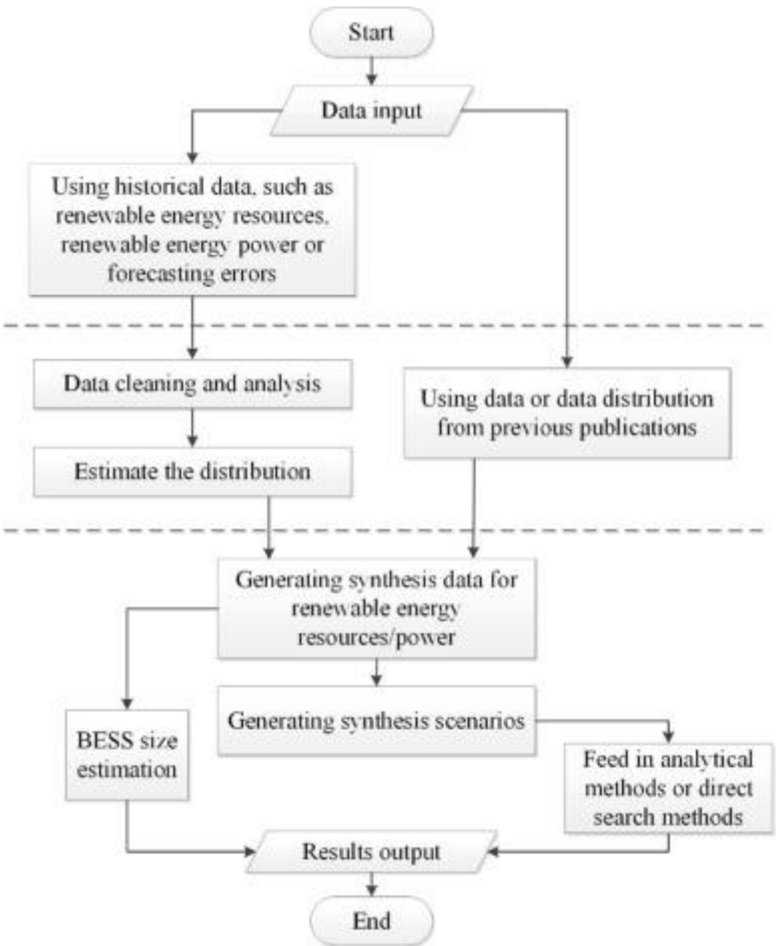


Figure 1: Flowchart of probabilistic methods

Probabilistic methods have the advantage that the need for a large amount of resource data is lessened, making them useful for situations with limited data availability. One key drawback is that the number of performance criteria being optimised in these approaches tends to be small (often only one or two), which makes their applicability for detailed designs limited. A typical approach is to construct models of the generation capability of the RE power system in question and combine them with a load model in order to create a risk model of the power system. Performance criteria can then be optimised against this risk model. One straight-forward approach based around this process is to use statistical methods to generate simulated samples as in Wu et al., where a mixed distribution based on Laplace and normal distributions was used to model forecast errors of a single wind farm over multiple timescales [30]. Global Horizontal Irradiance (GHI) data of solar irradiance have also been generated through a Markov-chain approach for battery size determination, as detailed in [25].

Besides implementing **probabilistic methods for data generation**, **stochastic optimisation methods** have also been deployed in many studies. The most popular of these is the Monte Carlo approach, in which a large number of scenarios (samples) are generated according to the statistical behaviour of random variables. By surveying the outcomes from a large number of scenarios generated, the optimum configuration can be deduced. By its very nature, Monte Carlo simulation usually entails considerable computation, but it does offer a comprehensive strategy for making a design decision. Monte Carlo approach has also been used for the dual objectives of demand shift and outage protection in building integrated PV systems considering uncertain building load, weather information and local historical outage distribution [31]. Other applications of Monte Carlo approach for battery storage includes minimising the power imbalances from inaccurate wind forecasting considering the uncertainty from forecasting [32], and frequency control with regards to statistical data of wind speed, solar irradiance and load [33]. Apart from the Monte Carlo approach, chance-constrained optimisation [34], robust optimisation [24] and stochastic control strategy [35] have also been employed to determine the size of the battery system taking into account uncertain random variables.

2.2.2 Analytical methods

Analytical methods, sometimes referred to as deterministic methods, are amongst the most broadly used methodologies for BESS size determination. These methods are based around analysing a series of power system configurations with the system elements varied being those that need to be optimised against performance criteria. A flow-chart explaining analytical methods can be found in Figure 2.

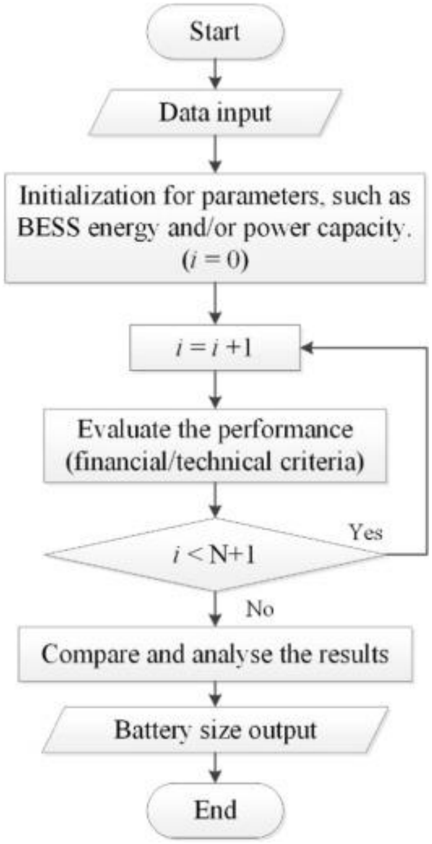


Figure 2: Flowchart of analytical methods

Analytical methods can be very straight-forward, such as when sizing for absorbing spilled wind energy, the battery's power and energy capacity can be derived directly from its daily spilled wind power profile [36]. Another simple example includes battery sizing for a constant windfarm output [18]. However, analytical methods are typically implemented by repetitive calculations or simulations performed over fixed intervals for the relevant system elements (usually the varying power and energy capacity). Using this approach, where performance for varying sizes of the battery storage against the corresponding performance criteria (financial or technical metrics) are found, a selection for battery sizing can be made. Another similar example is to conduct a sensitivity analysis to observe the impact of different battery sizes over performance criteria (financial or technical metrics), such as the battery sizes over the payback periods in [37]. The detailed implementation of specific strategies in different studies varies considerably in terms of the underlying system models. These can be based on numerical models, where the relationship between battery capacities and the assessed criteria can be directly formulated by equations. Dynamic models, where relationships are typically represented by differential equations requiring sophisticated numerical techniques to solve, are also included. Professional software is often used for the simulations of dynamic cases. A good illustrative example of applying analytical methods through a numerical model is given in Rodrigues et al. [15], in which several simulations with varying battery capacities were performed, analysing the annualised cost of corresponding storage systems and wind power curtailment. Using these techno-economic indicators, the size of the battery system can be chosen. Other examples include Aghamohammadi et al., in which a number of dynamic simulations were performed with decreasing the allowable overloading coefficients for primary frequency control, until the BESS is able to capture the frequency mismatch, a condition indicating an optimum battery size [29]. Whilst the use of analytical methods is very effective in many cases, a key concern is the need for a large number of simulations with combinations of single/multiple techno-economic performance indices. This inevitably leads to a trade-off in the resolution of the solution, since, while it is obvious that smaller intervals would lead to more accurate results, the quantity of computations will generally increase at an exponential rate. This becomes problematic when limited computational resources are available, and can, in extreme cases, make the calculation of the full solution space untenable. From this point of view, improvements in high performance computing to improve the efficiency of large quantity computational simulations may allow for the use of analytical methods at higher resolutions [38, 39].

2.2.3 Direct search-based methods

An obvious refinement to analytical methods is to reduce the need for simulations across the entire configurational space of the system being analysed to reach the optimum solution in a computationally efficient manner. There is a vast array of techniques developed for such optimisation problems, with many of them being used for BESS sizing. These can be conveniently split into **mathematical optimisation techniques**, based on mathematical properties of the solution space, and **heuristic techniques**, where tailored search parameters can be used to deliver an efficient algorithm, often based around nature inspired selection methods. A flowchart demonstrating direct search-based methods can be found in Figure 3.

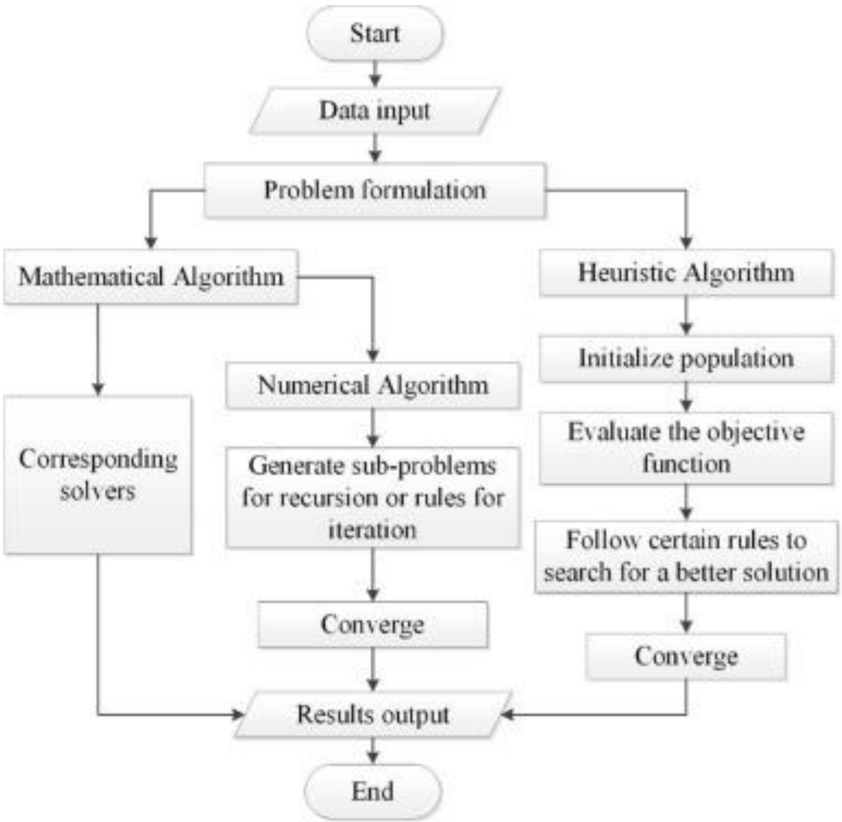


Figure 3: Flowchart of direct search-based method

2.2.3.1 Mathematical optimisation based methods

From the perspective of mathematical optimisation theory, BESS sizing optimisations may be expressed as **linear programming, mixed-integer programming or even non-linear programming problems**. Performance of BESS using these methods consists of constructing an objective function, which can be assessed by an iterative process that stops when the best result is reached. Optimisation problems can also be solved using classic numerical methods such as interior point algorithm, gradient descending algorithm, or Newton's method. These methods can find the solution in a limited number of steps, reducing computational load considerably. Moreover, due to the relatively mature nature of these methods, professional software is available for solving optimisation problems, such as MATLAB optimisation toolbox and General Algebraic Modelling System (GAMS) amongst others. For example, the study performed by Bahramira et al. was an application using IBM ILOG CPLEX Optimisation Studio (CPLEX) to optimise the size of an ESS which was formulated as a mixed-integer programming problem [21]. One significant case of using recursive techniques is dynamic programming (DP), which can solve optimisation problems through the construction of solution sets from the solutions of smaller sub-problems. DP has been applied in many studies for a spectrum of targets, including to minimise daily total cost [7] and to maximise expected daily operating profits [27]. It must be stressed, however, that while the application of these mathematical optimisation techniques can vastly improve computational efficiency, when the formulation becomes more complex, especially for non-linear programming problems, these tools face difficulties in converging to an optimum solution. This issue of robustness has led to the widespread use of heuristic-based solution methods as detailed below.

2.2.3.2 Heuristic methods

Heuristic methods **allow non-optimal or not perfect (usually near optimum) solutions**, which are sufficient for practical purposes. The distinct advantages of heuristic methods are that they can avoid complicated derivatives, especially for non-linear optimisation problems, thereby using reasonable memory and computation time [40, 41]. Despite often having no mathematically proven basis for obtaining optimal solutions, heuristic approaches such as nature-inspired algorithms like **Genetic Algorithms** (GA), **Particle Swarm Optimisation** (PSO), and **Tabu searches**, etc., tend to offer fast convergence, simple implementation and strong flexibility. In fact, there are many previous studies solving BESS size determination problems by using nature-inspired algorithms. For battery sizing problems, PSO has been proven to be a popular algorithm to solve for minimising the cost of energy not supplied and ESS costs (mixed-integer nonlinear programming) [42] and to minimise the levelised cost of electricity [43]. Other heuristic algorithms such as genetic algorithm based methods [10], Tabu search [44] and **bat algorithms** (BA) [8] that are nature inspired evolutionary techniques are also actively applied for battery size determination.

2.2.4 Hybrid methods

The sizing techniques outlined above each have their own specific advantages for the BESS sizing process, along with weaknesses. For example, while analytical methods usually return more accurate results, a poorly selected optimisation interval may miss the exact solution, or a high resolution may increase the computation burden significantly. Also, search-based methods may not guarantee an optimal result due to the possibility there is a convergence to a local optimum, rather than to the global optimum. Moreover, when using probabilistic methods, a large quantity of scenarios are generated, which may place a heavy burden on computational capability. It stands to reason that if the advantages of different methods can be combined to enhance the effectiveness and efficiency of the optimisation procedure, whilst simultaneously removing inherent weaknesses, these so-called hybrid methods should deliver both robust procedures and the ability to ensure the global optimum being guaranteed with the required resolution. The hybridisation of different methods can occur in either a de-coupled or coupled way, where de-coupled indicates that two optimisation methods are mutually exclusive processes, whereas coupled suggests two methods working together concomitantly. An example of a decoupled application of hybrid methods is given in Cervone et al. [25], where both a probabilistic method and an analytical method were used to determine the BESS size for a grid-scale PV plant in separate steps. A discrete-time Markov Chains approach was first implemented to generate a 20-year time series of irradiance, then an economic analysis of various energy storage systems was used to reduce the imbalance costs associated with renewable energy integration, thereby obtaining the optimal size of the battery system [25]. This approach is in contrast to the coupling of probabilistic and search-based methods via robust mixed-integer linear programming that Dragicevic et al. implemented for minimising the overall investment cost considering the uncertainty of PV, wind energy and demand [24]. Another example of coupled hybrid methods was the use of a chance-constrained stochastic optimisation model, where a Monte Carlo embedded Differential Evolution (DE) algorithm was applied as a solver to maximise wind power utilisation and minimise the investment and operation costs as reported by Zhang et al. [34]. In summary, there has been a **wide range of approaches implemented when solving the problem of battery sizing**. In Table 1, the advantages and disadvantages of sizing techniques mentioned are summarised. The tailored simulation cases in each study can make it difficult to compare the effectiveness of each of the different methods, but there are some studies comparing between techniques. For example, both analytical and search-based methods were performed to minimise the battery power for load shedding in Kerdphol et al. [45]. Their results showed that the optimal battery power capacity based on search-based methods showed better frequency and voltage performance than the capacity found using analytical methods. However, it must be cautioned that this is one case, and it does not mean that search-based methods should be regarded as superior to analytical methods for all purposes. Overall, BESS size determination in RES can be seen to be a multi-faceted problem, involving single/multiple-objective optimisation, decision-making and multiple systems simulation. It should also be noted that more advanced solution techniques are being continually developed with these potential new hybrid methods combining advantages from different optimisation approaches.

Table 1: Summary of the pros and cons of BESS sizing methods

Method	Pros	Cons
Probabilistic • Generates synthetic weather resources and PV/wind power generation data • Generates synthetic scenarios for stochastic optimisation	• Overcomes the restriction of limited data availability • Gives results with confidence levels	• Accuracy relies on the availability of historical data • May require computational extensive resources
Analytical • Direct calculation based on intuitive criteria • Repeated computation/simulation with fixed intervals • Sensitivity analysis	• Better visualization with the change of battery sizes • Strong flexibility for all criteria and simulation environments	• Computational intensive • May miss global optimum if the data resolution is not high enough • Requires large amount of representative input data
Mathematical optimisation • Linear, mixed-integer, quadratic programming problems • Problems that can be linearized • Problems that can be solved by numerical methods	• Strong capability to find the global optimum • Fast convergence and high robustness for linear problems	• High efficiency limited to linear/mixed-integer/quadratic programming problems • Linearization may require extra derivations • Explicit mathematical formulation required
Heuristic • Non-linear optimisation problems • Apply nature-inspired algorithms such as GA, PSO, Tabu search and Bat Algorithms	• Strong flexibility to solve all optimisation problems • Avoid complicated derivatives • Use less computational resources • Simple implementation • Large assortment of algorithms	• May converge in local optimum instead of global optimum • Less robustness and accuracy for linear problems
Hybrid • Decoupled methods combined sequentially • Hybridisation of different methods in a coupled way	• Combines strengths of different methods • Improves robustness and ensures global optimum found	• Likely to increase the complexity • May require high computational resources than heuristic methods

3 An analytical method implemented for sensitivity study purposes

One of the major objectives of this study is to provide to project investors and designers useful synthetic information on the most influencing factors to consider during the BESS sizing procedure. For this purpose, some sensitivity analyses need to be performed to assess how the value of BESS sizing criteria (financial and/or technical metrics) may be affected by a change of influencing parameter, potentially leading to a different optimal size determination. To conduct this survey, an **analytical method has been implemented**, based on numerical simulation. Although this type of deterministic technique involves significant computational resources to repeat simulations with different combinations of BESS sizes and influencing factors parameters; it provides the necessary flexibility for all criteria and parameter settings required by the sensitivity analysis. Due to deterministic calculation on user-specified intervals, it also **enables a better control and visualization of the impact of the factors variation**, as already mentioned in section 2.2 and Table 1.

3.1 General description of the deterministic simulation-based method

The method implemented for BESS optimal sizing relies on a numerical simulation platform called SPIDER (Simulation Platform for the Integration of Distributed Energy Resources), which has been developed at CEA in a Matlab / Simulink environment.

The main advantages of using this simulation tool both to carry out some techno-economic assessments as required by the BESS optimal size determination and to perform a sensitivity analysis are listed below:

- The Simulink graphic-modelling environment enables to **reproduce the functional architecture** of the study cases by hierarchical blocks and diagrams and to interface the energy system components models with the control algorithms.

- This platform environment offers a **high-level of modularity**, enabling to run some similar operation scenarios with **different control algorithms** and/**or different degrees** of technical **modelling** for a same energy **component**, just by switching the corresponding block model in the Simulink use-case diagram. For the present study, this modularity enables to carry out some sensitivity analyses on the type of the battery model used for the calculation of its optimal size. Thus, the optimal sizing results obtained with an in-depth performances battery model based on equivalent-circuit equations will be compared with those obtained through a simplified modelling of the energy/power behaviour of the battery. The influence of the control strategy on optimal sizing will also be assessed through the comparison of battery size determination when a basic or more advanced level of control is integrated into the energy management algorithms.

- The SPIDER platform benefits from an **already existing library** of energy component models (PV plants, wind turbines, energy storage systems, battery cells, converters, fuel generators,…) and control algorithm templates developed by CEA. By reusing these generic modules, the study can more intensely focus on the specific issues related to optimal sizing and on the comprehensive sets of configurations / parameters to be implemented for the sensitivity analysis purposes.

- The SPIDER platform provides a **generic structure** and a ready-to-use **set of templates, functions and tools** for configuring simulations, launching some sensitivity analysis scenarios and customizing post-processing calculations, as well as instantiating the models with some specific set of parameters of the case study.

- The ability to run **simulations at different time steps**, specified by the user as a configuration parameter. The sensitivity study will take advantage of this flexibility to also analyse the influence of the simulation time-step on the optimal sizing results. The repetition of similar operation simulations with different time-step values (typically 1mn, 10mn and 1 hour) should indeed provide a better understanding of the impacts of intermittency and limited predictability of renewable energy sources on the optimal sizing results. This analysis axis could also help to find a convenient trade-off between required computational time and accuracy of the result.

The general synoptic implemented for the calculation of the optimal sizing criteria of a given configuration (i.e. one particular size of BESS) is depicted on Figure 4. By repeating this procedure for different BESS configuration sizes, it becomes possible to identify which configuration size leads to the best value of the performance indicator, determining thus the optimal size.

In practice, the optimal sizing tool developed into the SPIDER platform enables to define a range of BESS size values for launching the automatic processing of the defined sizing indicators on the entire search area. At the end of this processing, an overview graphic is produced to visualize the variation of the sizing criteria along with the BESS size (as illustrated on Figure 5), as well as synthetic tables containing all values of intermediate and final indicators for each of the simulated configurations.

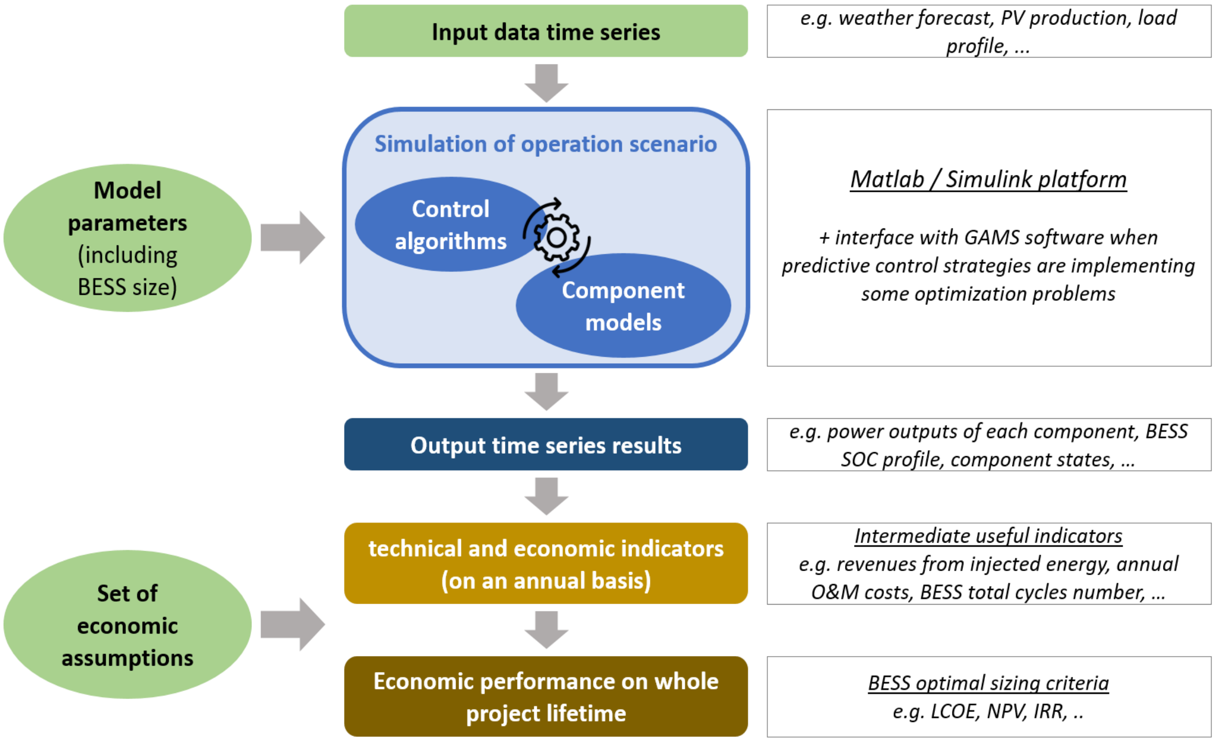


Figure 4: Overview of the deterministic method used for BESS optimal sizing

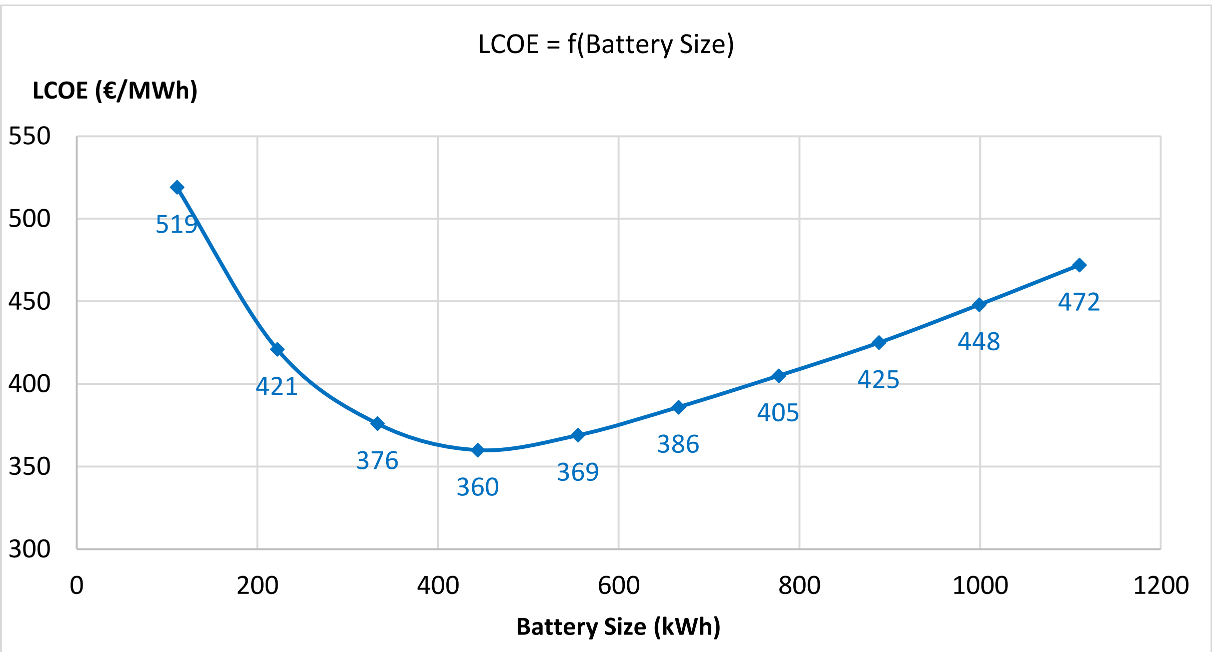


Figure 5: Example of results where optimal sizing criteria used is LCOE

On this figure, minimal LCOE value (360€/MWh) is obtained with the battery nominal capacity of 440 kWh, which is the BESS optimal size in this case.

3.1.1 Data set required for simulation

As shown on Figure 4, 2 types of data set are required to launch the simulation process: input data time series and model parameters. The following sections give a brief description of each of them.

3.1.1.1 Input data time series

This type of dataset is used to simulate the conditions where the system has to operate in terms of external constraints. For energy applications involving some renewable sources, these data are typically composed of information enabling to determine the renewable energy source potential as well as the eventual load demand constraints. As these constraints (energy generation potential and/or load demand profile) have of course a direct impact on the required BESS size, accurate estimations or even better real historical measurements specific to the real installation and location must be used.

For the 2 illustrative application cases developed in next sections and used for sensitivity analysis, the need for input data time series was as follows:

- **PV power output:** the PV power output can be computed from data of different nature, like solar radiation and temperature from the site location, and then processed according to the PV plant characteristics (solar panels azimuth, tilt angle and specifications). However, it may be more convenient to directly use the power production (DC or AC) of one module or several modules if it has been measured or computed by another tool. For the present study simulations, a full-year measurement (1mn resolution) from a PV plant located in Corsica island has been used. Once normalized for 1 kWc of PV installed capacity, it could then be scaled to the application specific configuration and imported as time series input. To take into account the degradation of PV performance over time in simulations of several years, an annual PV degradation rate is applied (a median degradation rate for PV modules of 0.5% per year is commonly admitted).

- **PV production forecast:** some PV production forecasts related to the PV output power mentioned above were necessary for one of the applications and for the enhanced predictive control algorithms used in the sensitivity study. As real historical forecasts may be difficult to obtain, they are often subject to rough estimates. Most basic approaches consists of exploiting the PV power output historical data either to build a "**perfect forecast**", i.e. by considering that the PV forecast for day D+1 is exactly the PV production that will occur on day D+1, or a "**24h persistence forecast**", assuming that the PV forecast for day D+1 is the production realized on day D. It is also possible to use more complex probabilistic methods to define some **stochastic PV forecast time series** computed from the PV real production data. In any cases, the subject here is related to forecast errors, and it raises the question of their degree of impact on BESS optimal sizing.

The time-series used for PV production forecast in this study correspond to real historical PV forecasts related to the PV production of the Corsica solar plant, based on meteorological prediction. As they are available for several time horizons (from day D-3 to day D-1), the study benefits from realistic forecasts of different quality, which can be used to assess the influence of forecast errors on the optimal BESS size determination.

- **Load power profile:** for the second application case illustrated in this methodological study and detailed hereafter (section 4.2), the electricity demand power profile of an industrial load is needed. As for PV production, the most realistic profile is obtained by collecting some historical power measurements of the real equipment. In our application case, the industrial load has a weekly consumption profile, repeating from one week to the next with some slight deviations. As no full-year measurement was available, some full-week measurement samples were extracted from the available historical data and randomly duplicated to form a one-year realistic profile.

3.1.1.2 Model parameters

The model parameters correspond to the dataset which is used to define the behaviour of the component models. For a given component, the nature of the model parameters strongly depends of the type of model used, whereas their values depends of the specific technology or specific equipment for which the simulation has to reproduce the operation.

For the study key component which is the battery system, a widely used battery Li-ion technology had been modelled and associated with a DC/AC converter component model. The battery system size metrics, which need to be incremented during the optimal sizing determination process for associating performance values to each BESS size of the selected range, are defined through the model parameters. A given BESS size corresponds to the kWh/kW combination of an energy nominal capacity (in kWh) and a rated power (in kW). The energy nominal capacity can be changed by the parameters setting the numbers of Li-ion battery modules in series/parallel put together (within the constraint of compliance of the resulting battery DC voltage to the converter voltage input range), whereas the rated power depends both on the battery architecture assembly (series/parallel) and the DC/AC converter nominal, which is chosen accordingly to the application technical constraints.

As introduced in section 3.1, two different approaches for modelling the Li-ion battery technology, internally developed at CEA, will be compared in the BESS optimal sizing exercise, leading to parameters of different nature for the BESS model:

- For in-depth performances battery modelling based on **electrical equivalent-circuit** equations, denoted as EC_model through the present document, the battery electrochemical behaviour is reproduced from a large set of electrical values parameters, consisting of several data tables of battery open circuit voltage and resistance values, characterized in laboratory under various conditions of current, temperature, state-of-charge or state-of-health. The EC_model used in this study also integrates a SOH computation module, able to estimate the battery capacity degradation at each simulation time-step from ageing lab-extracted parameters (cycling and calendar ageing) specific to the chemistry of the battery cell selected for the simulation.

- For simplified **modelling of the energy/power** behaviour of the battery, denoted as E/P_model through the present document, the model parameters basically consist in a correspondence table which directly gives the BESS energy efficiency as a function of the AC power setpoint applied to the storage system. In contrast with the EC_model, the E/P_model used in this study does not compute any SOH estimations. No ageing model parameters are therefore specified for the simulations with the BESS E/P_model.

Among the factors which will be investigated through the sensitivity analysis to assess their impact on the BESS optimal sizing, some of the them are directly related to model parameters, such as BESS efficiency or capacity degradation over time due to battery ageing. For those, the sensitivity study will therefore consist in repeating similar simulation scenarios with different parameters datasets to observe their influence on the optimal size computation and address the following questions:

- **BESS efficiency parameters influence**: What is the difference observed between the use of a precise variable efficiency dataset (efficiency varying according to temperature, SOC and applied power) and the use of a constant mean efficiency value? How the optimal sizing result is affected by an approximation of the BESS efficiency profile?

- **BESS ageing parameters influence**: What is the impact on optimal sizing of taking into account the battery performances degradation over time? In case of limited availability of accurate battery ageing data, could it be a correct workaround to perform the simulations over the project lifetime with a constant but moderately degraded battery capacity?

3.1.2 Simulation processing

Once data input time series have been imported and model parameters instantiated within the platform, the simulation of the operation scenario can be launched. The simulation processing is performed through a Simulink layout dedicated to the application case. Figure 6 gives an example of such a simulator diagram. It basically consists, from a functional point of view, in connecting two entities: the control module and the plant model.

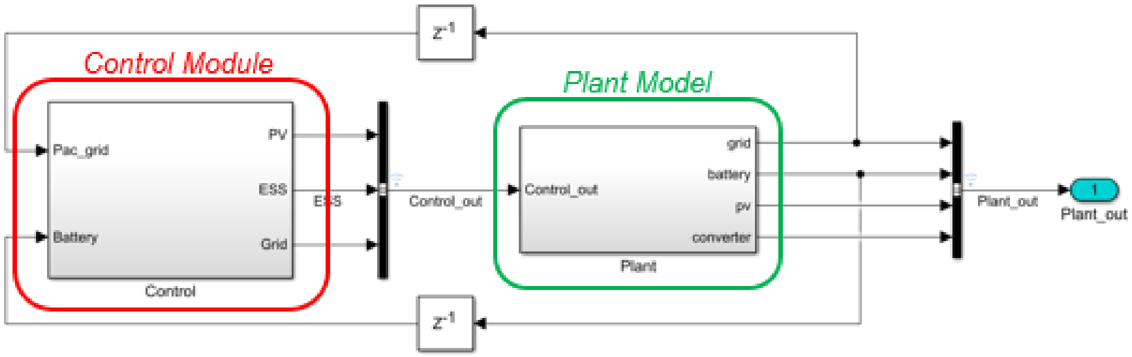


Figure 6: Example of case-study simulator within the SPIDER platform

On the one hand, the control module has the function of EMS (**Energy Management System**) for the application. This module integrates all control algorithms dedicated to the calculation of setpoints to be applied to the different controllable components composing the energy simulated system. Depending on the complexity of the implemented control, this control module may contain several algorithms blocks and subsystems organized in hierarchical levels, from the high level control for planning (EPM module: Energy Planning Module) taking into account for instance forecasts up to the low level control for manageing the power setpoint for the current time step (PMM module: Power Management Module).

On the other hand, the plant model corresponds to the modelling of the physical part of the installation and contains all the necessary component models, such as those for energy storage systems, PV panels, converters, etc.

As illustrated in Figure 6, the setpoints to be applied on the components are transmitted from the *Control Module* block to the *Plant Model* block (*Control_out* signals); and in the opposite way, the *Plant Model* block communicates the necessary set of component states and power profiles to the *Control Module* block, such as the power injected to the grid or the state of charge of the batteries.

Bringing together the control module and the plant model in the specific context of the application external conditions (input data time series) enables the simulation to reproduce the operation scenario in terms of setpoints computed by the control algorithms and induced behaviour (power profiles) of the energy system components.

At the end of the simulation process, raw results consists in the simulation output time series, i.e. all logged output signals from the control module and the plant model: BESS power profile, grid injection power output, PV curtailment activation profile, battery state-of-charge values along the simulation duration, etc. These output time series correspond to the sequence of values taken by each logged variable over the simulation duration, their resolution is equal to the time step used for the simulation.

The next and final step of the optimal sizing method (see Figure 4) aims to exploit the raw simulation results to compute the relevant key performance indicators which enable to make a decision on the optimal BESS size. These post-processing calculations are described in next section.

3.1.3 Post-processing calculations

The purpose of post-processing for optimal size determination is to associate a performance value to each simulated configuration, enabling to **have a common comparison criteria** and identify which configuration, i.e. which size of BESS, is the best solution.

Among the different categories of sizing criteria discussed in section 2.1, financial indicators are the most commonly used. They have the advantage of easily enabling the comparison of different alternatives through a common unit, and can be directly integrated in discussions with project investors for evaluating financial return and making decisions.

BESS sizing criteria used in the present methodology are based on financial indicators, with the setting of a comprehensive techno-economic assessment to balance the economic value of the rendered service and the total system costs. It relies on the calculation of total system expenses and incomes. Incomes are application dependent since they may come from sales on energy markets, green certificates, feed-in tariffs, etc. For each component, expenses are obtained by summing up investment, total O&M and total replacement costs. O&M costs are applied each year and replacement costs are applied when equipment estimated life span is expired. The total system expenses are obtained by summing up expenses of all components. To enable proper comparison between the different configurations independently of the project lifetime, the residual financial value of the BESS at the end of the project is calculated and deduced from the total amount of expenses.

The most appropriate financial indicator for BESS sizing criteria should then be chosen in regards to the purpose of the application. For standalone systems or generation units, LCOE **(Levelized Cost of Energy**, expressed in €/MWh) is generally well suited as it estimates the average cost of produced energy. But when the energy application is designed for more complex market rules where variable feed-in tariffs may be applied or ancillary services may be remunerated, other financial indicators like NPV (**Net Present Value**) or IRR (**Internal Rate of Return**) may be more suitable. Illustration of these different choices of financial indicator as sizing criteria will be given in the two illustrative use-cases developed in section 4.

Table 2 below lists the implemented BESS sizing criteria and their definitions.

Performance criteria	Formula	Details
Levelized Cost of Energy Determine the average net present cost of electricity generation over the project lifetime	$\boldsymbol{LCOE} = \frac{\sum_{n=0}^{N} \frac{CAPEX_n + OPEX_n}{(1+r)^n}}{\sum_{n=0}^{N} \frac{E_n}{(1+r)^n}}$	$CAPEX_n$: total investment costs of year n $OPEX_n$: total O&M costs of year n E_n : total electrical energy generated in the year n r : discount rate N : project lifetime

Performance criteria	Formula	Details
Net Present Value Determine the present value of all future cash flows generated by a project, including the initial capital investment	$\boldsymbol{NPV} = \sum_{n=0}^{N} \frac{CF_n}{(1+r)^n}$	CF_n : cash flow (difference between incomes and expenses) of year n r : discount rate N : project lifetime
Internal Rate of Return IRR is defined as the discount rate that makes the NPV equal to zero	$\sum_{n=0}^{N} \frac{CF_n}{(1+\boldsymbol{IRR})^n} = 0$	CF_n : cash flow (difference between incomes and expenses) of year n IRR : internal rate of return N : project lifetime

Table 2: BESS sizing criteria used in the study

To be able to compute these final key performance indicators according to the formula presented in Table 2, some annual intermediate indicators need to be calculated from the simulation output time series results, such as the amount of yearly electrical energy generated, annual incomes, total operation costs including replacement costs when necessary, etc.

Furthermore, this financial evaluation requires a **set of economic assumptions** that allow realistic estimates of investment, O&M and replacement costs for each component and that include a discount rate value close to the WACC (Weighted Average Cost of Capital) generally observed in the business field of activity of the project. It is worth mentioning that all optimal sizing indicators values computed in this study are highly dependent on this set of economic assumptions.

3.2 Sensitivity study scope

To provide to project investors and designers a better understanding on the most influencing drivers to consider during the BESS sizing procedure, a sensitivity analysis has been carried out for assessing the impact on BESS optimal sizing of several factors.

This study has been performed through the described simulation method, using the 2 illustrative use-cases described in section 4. To sum up the different areas explored by the sensitivity analysis, Table 3 below lists the different factors which have been investigated with their comparative simulation scenarios.

Influencing factor	Face to face scenarios	
Precision of the BESS efficiency behaviour	*Baseline*	BESS model parameters include tables of precise efficiency values varying according to temperature, current and SOC
	Comparative	BESS efficiency is set up as a constant value (average efficiency)
Degradation of battery capacity due to ageing	*Baseline*	BESS model parameters include ageing data enabling the simulation to take into account the battery capacity degradation over time
	Comparative	Battery capacity remains constant over time
Degree of technical modelling of the BESS component	*Baseline*	In-depth performances battery modelling based on equivalent-circuit equations (EC_model)
	Comparative	Simplified modelling of the energy/power behaviour of the BESS (E/P_model)
Simulation time-step	*Baseline*	Time-step of 1 mn
	Comparative #1	Time-step of 10 mn
	Comparative #2	Time-step of 1 hour
Degree of complexity of control algorithms	*Baseline*	Basic control algorithms
	Comparative	Advanced control algorithms (including optimization)
Forecast quality when predictive control is facing forecast errors	*Baseline*	PV: standard day-1 forecast Load: persistence day+7
	Comparative #1	PV: perfect forecast (actual PV production) Load: perfect forecast (actual consumption)
	Comparative #2	PV: enhanced forecast with 50% fewer errors Load: enhanced forecast with 50% fewer errors (average between baseline and perfect forecasts)

Table 3: Sensitivity analysis scenarios

4 Illustrative application use cases

The method implemented and the sensitivity study have been carried out for 2 different illustrative BESS application use cases:

- **BESS application #1: PV smoothing and peak shaving**, for which the overall objective is to sell PV energy to the grid under several injection constraints. The details of this first use case are given in section 4.1.
- **BESS application #2: Hybrid microgrid,** for which the overall objective is to entirely satisfy the electricity demand of an off-grid industrial load. The details of this second use case are given in section 0.

The fact of using these two very different use cases in this study has two advantages:

- Firstly, it enables to illustrate how the generic methodology developed in this report can be adapted to different use cases, for systems composed of various energy components and/or energy application purposes leading to define different sizing criteria,

- Secondly, it helps to differentiate, among the influencing factors investigated through sensitivity analysis, those whose impact has the same magnitude regardless to the application from those whose impact is application-dependent.

4.1 BESS application #1: PV smoothing and peak shaving

4.1.1 Application description

This application case corresponds to the call for tenders issued by the French Energy Regulatory Commission in 2015 for installing PV solar plants in French Non-Interconnected Islands. The full description of the call for tenders can be found on the French Energy Regulatory Commission website [46].

For these grid-connected PV power plants, an energy storage system must be used in order to control the power injection to the grid and to store some produced PV energy.

A minimal capacity of the storage system is imposed by the call for tenders, set to 0,5MWh useful capacity per MW of installed PV peak power, at any time of the project life. To respect this constraint, the battery nameplate capacity must be chosen a little higher, to take into account both the deep of discharge (DoD) range and the capacity degradation due to ageing. In our study case, with a DoD of 90% and a capacity degradation up to 30% before battery replacement, the minimal nominal capacity should be set to:

$$rated\ capacity_{min} = \frac{useful\ capacity_{min}}{0.9 * (1 - 0.3)} = \frac{0.5}{0.9 * 0.7} \approx 0.8\ MWh\ per\ MW\ of\ PV$$

In order to sell the injected energy at the agreed feed-in tariff, the following main constraints must be respected:

- **Power injection profile must be announced in advance**

  - The daily injection profile must be known in advance (the day before, at 16h00 at the latest) by the grid operator and the producer shall respect it (outside a tolerance range of ±5% of the installed PV power (Ppeak), some financial penalties are applied). It has to be noted that the need to announce the profile the day before means that a PV production forecast for the day D+1 is necessary on day D.

  - The producer may update the injection plan 3 times during day D (according to updated weather forecast for instance) but only at precise time-slots defined as follows:
    - before 4h: possible delivery of an updated plan for period [6h00 ; 23h59]
    - before 10h: possible delivery of an updated plan for period [12h00 ; 23h59]
    - before 14h: possible delivery of an updated plan for period [16h00 ; 23h59]

- **PV smoothing: the PV fluctuations must be limited to specific ramp rates**

  The values of maximum rates for power increase and decrease are defined as follows, according to specific periods in the day:

Period in day	Ramp rates to be respected
0h00 – 10h00	Power increase at a rate not greater than 0.6% of the PV installed capacity (Ppeak) per minute Power decrease at a rate not greater than 0.3% of the PV installed capacity per minute
10h00 – 14h00	Power increase and decrease at a rate not greater than 0.3% of the PV installed capacity per minute
14h00 – 19h00	Power increase at a rate not greater than 0.3% of the PV installed capacity per minute Power decrease at a rate not greater than 0.6% of the PV installed capacity per minute

Table 4: BESS application#1 - Maximum ramp rates values for injection to grid

- **Peak shaving: power injection during peak period**

  In order to contribute at the mitigation of the daily peak power demand, the PV solar plant including the energy storage system must inject energy every day during the two hours of the peak period (19h00 – 21h00) at a minimum power output of 20% of the PV installed capacity (20% of Ppeak). For the energy injected to the grid during the peak period, a bonus equal to 200€/MWh is added to the agreed feed-in tariff.

To sum up, the requested operation is illustrated on Figure 7 and Figure 8. Figure 7 illustrates the planning rules to be observed when announcing the power injection profiles, whereas Figure 8 gives an example of PV production and resulting grid injection profile for a typical clear day.

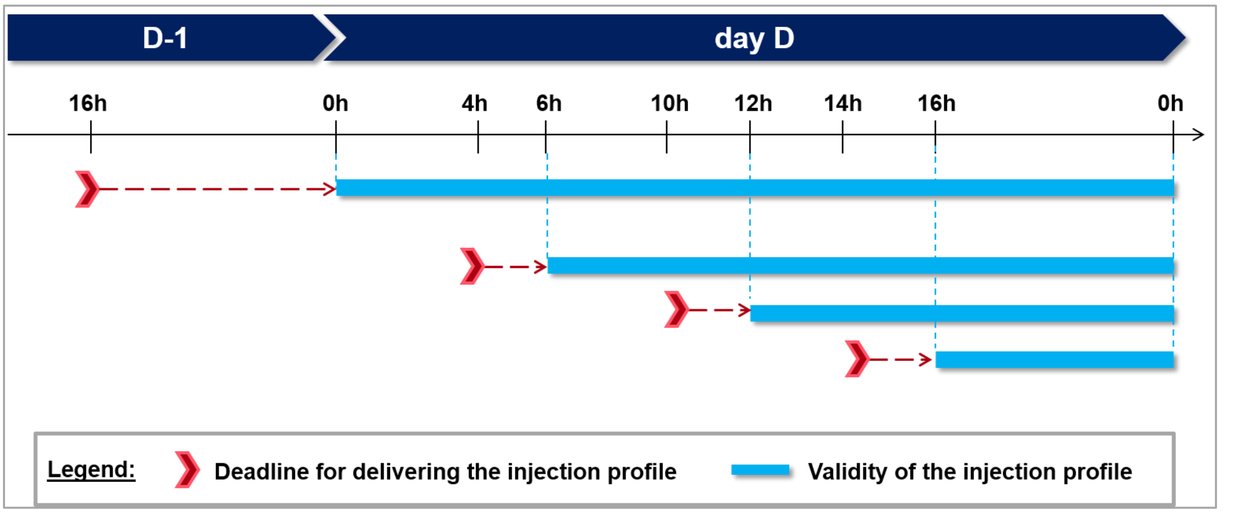


Figure 7: BESS application#1 - Planning rules for grid injection announcement

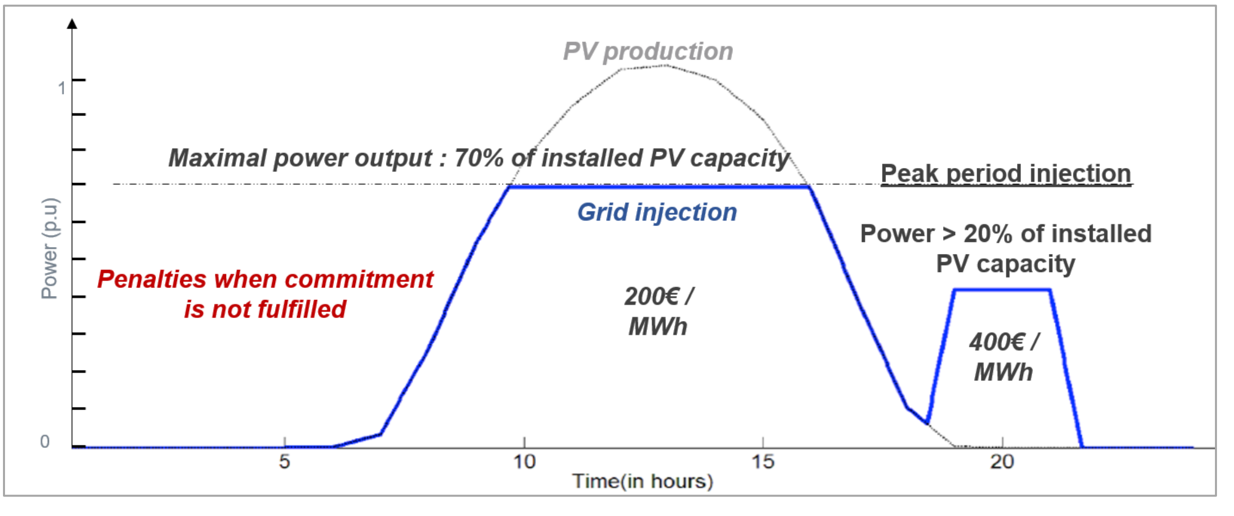


Figure 8: BESS application#1 - Example of a daily injection profile

On Figure 8, the illustrative feed-in tariff of 200€/MWh leads to a price of 400€/MWh during peak period due to the peak bonus of 200€/MWh.

4.1.2 Scenario configuration

The simulation scenario has been set up for a 1 MW PV plant and a BESS composed of Li-ion batteries, which storage total capacity is varying between approximately 800 kWh (minimal size imposed by the call of tenders) and 1300 kWh. The main component configuration parameters are listed in Table 5.

PV Plant	Installed capacity (peak power)	1 MWp
	PV degradation rate	0.5% per year
	PV producible dataset	1 year measurement data from a monitored PV plant in Corsica
	PV forecast dataset	1 year historical irradiance forecasts of the Corsica plant location
BESS	Battery technology	Li-ion / app. 6.5 kWh per battery module
	Depth of discharge	90% (from $SOC_{min} = 5\%$ to $SOC_{max} = 95\%$)
	Battery replacement	Replacement when SOH is 70%
	Battery capacity	From app. 800 kWh (minimal size imposed) up to app. 1300 kWh / 10 size configurations made of series/parallel modules assembly in coherence with converter DC voltage range
	DC/AC converter power	Up to 700 kVA

Table 5: BESS application#1 - System components setup

4.1.3 Simulation of operation

Figure 9 illustrates the simulation of the operation for a sequence of three particular days of the same year, which has been used for graphical verification of the correct behaviour of the simulated system:

- Day 1 is a sunny clear day with a typical bell-shaped curve for PV production
- Day 2 is a mixed day of alternating sunny and cloudy periods
- Day 3 is a very dull day with a heavy cloud cover

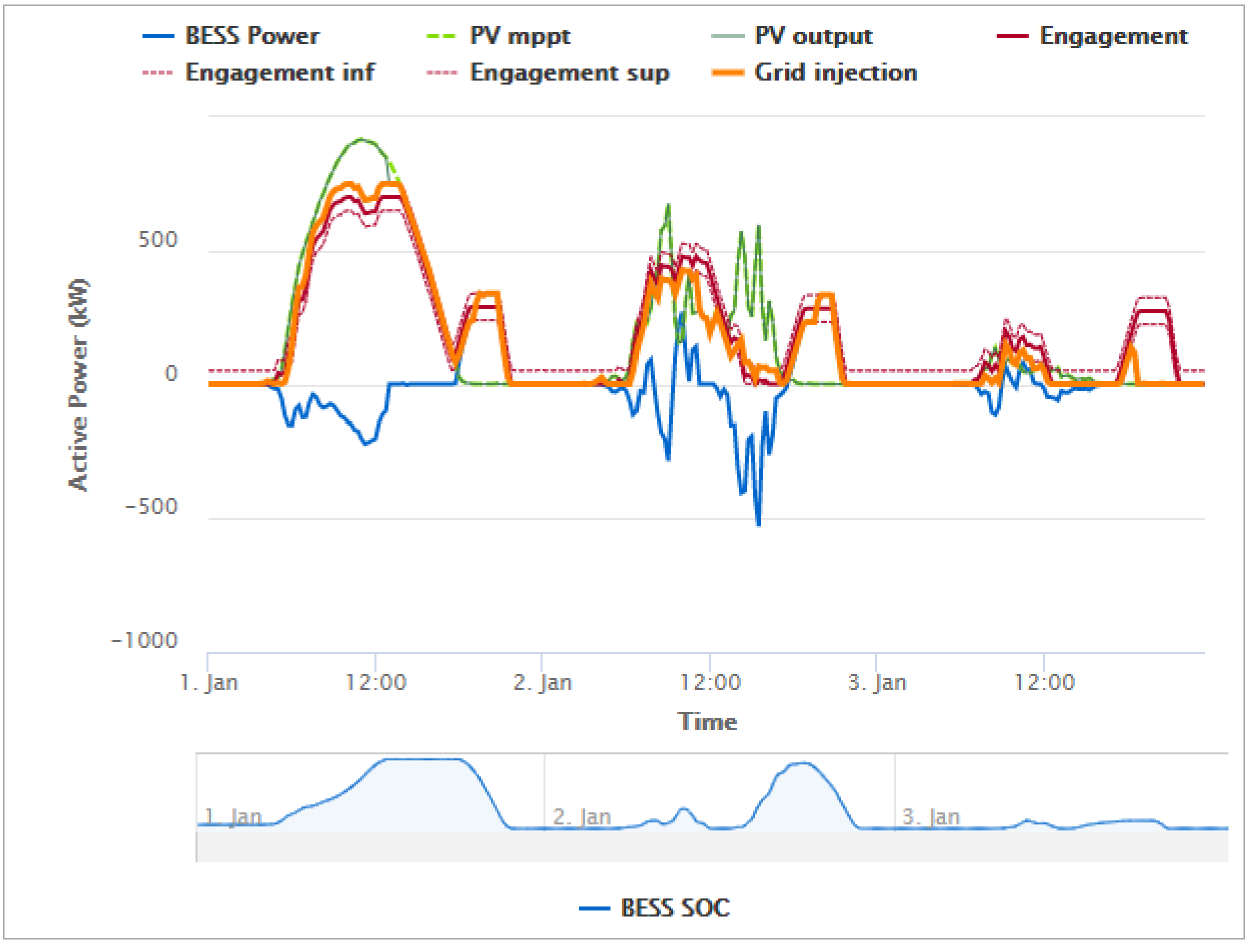


Figure 9: BESS application#1 – Illustration of simulated operation

This simulation figure shows that there are significant differences in operation, depending on the type of day.

- Day 1 (sunny) corresponds to the baseline expected behaviour: the PV production which is over the 70% injection limit is used to charge the battery (BESS power <0) during the day and then discharged during the peak period. The engagement is respected within the tolerance of ±5% (on this illustrative example, the injection profile is higher than the announcement, at +5% tolerance, because the PV forecast was a bit pessimistic for this day).

- For day 2 (mixed), it is noticeable that the battery has to discharge at the middle of the day to compensate the lack of PV, thus attempting to respect the engagement and avoid the penalties. Battery is rapidly empty (low SOC) and nothing can then be done to avoid penalties until there is enough PV production to charge again the BESS. PV production at the end of afternoon enables the battery to charge enough electricity to respect the engagement for the peak period in the evening.

- Day 3 (dull) corresponds to the worst case, for which PV production is so low that the BESS cannot charge enough energy to respect the peak period injection constraints, leading to a high level of penalties.

These noticeable differences emphasize the need of taking into account the full variety of day types when computing the optimal size of the BESS, rather than performing an estimation only on a standard day case or even on the worst case. The use of a full year PV production measurement is therefore of great interest for the optimal size determination.

4.1.4 BESS sizing criteria

The economic model of this application, for which the income arises from the sale of electricity at a specified feed-in tariff reduced by any penalties applied when the announced power profile is not respected, leads to choose to use the **NPV (Net Present Value) as the sizing indicator**.

In accordance with the NPV formula (reminded in Equation 1 below):

- The cash flow of year zero (CF_0) is defined as the total initial capital investment, i.e. PV plant and BESS procurement and installation costs,
- The cash flows of the following years (CF_n) are computed as the difference between annual incomes and expenses. The annual income corresponds to the amount paid by the grid operator during the year (sale of electricity reduced by any penalties applied). Annual expenses sum all OPEX costs for the specific year (O&M costs, including replacement costs when necessary).

Net Present Value Determine the present value of all future cash flows generated by a project, including the initial capital investment	$$\boldsymbol{NPV} = \sum_{n=0}^{N} \frac{CF_n}{(1+r)^n}$$	CF_n : cash flow (difference between incomes and expenses) of year n r : discount rate N : project lifetime

Equation 1: BESS application#1 - NPV indicator used as optimal sizing criteria

The economic assumptions used to compute the NPV indicator are listed in Table 6. They are based on several recent economic studies [47] [48] [49] [50] [51] about PV and storage.

Category	Designation	Value
Project	Project lifetime	20 years
	Discount rate	5 %
Initial investment	PV plant	825 € / kWp
	ESS battery & auxiliaries	350 € / kWh
	ESS converter & auxiliaries	200 € / kW
Electricity sale	Feed-in tariff	200 € / MWh
Operation costs	PV plant	Per year, 3% of initial investment
	ESS battery	Per year, 3% of initial investment

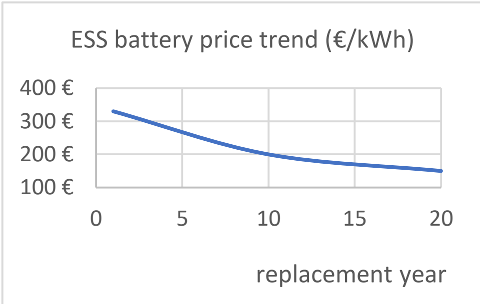
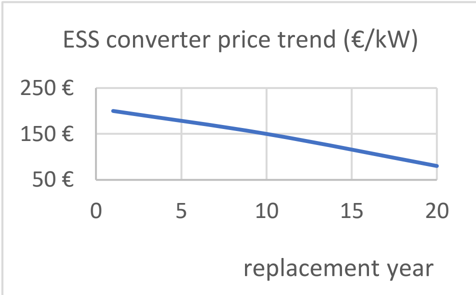
Category	Designation	Value
	ESS converter	Per year, 3% of initial investment
Replacement costs	ESS battery lifespan	Until SOH reaches 70%
	ESS battery replacement cost	Decrease trend over the 20 next years 
	ESS converter lifespan	10 years
	ESS converter replacement cost	Decrease trend over the 20 next years 

Table 6: BESS application#1 – Economic assumptions

4.1.5 Optimal sizing reference curve

Figure 10 depicts the NPV values obtained along the BESS sizes range explored through the simulations repetition process for the reference scenario. This reference scenario is summarized in Table 7: it consists in the combination of all baseline cases which were listed in Table 3 for the influencing factors sensitivity study description (section 3.2). The results obtained through this scenario are providing the most accurate values for sizing indicators, which will then be used as references in the sensitivity study comparisons to assess the impact of the investigated influencing factors.

Influencing factor	Reference scenario
Precision of the BESS efficiency behaviour	BESS model parameters include tables of precise efficiency values varying according to temperature, current and SOC
Degradation of battery capacity due to ageing	BESS model parameters include ageing data enabling the simulation to take into account the battery capacity degradation over time

Influencing factor	Reference scenario
technical modelling of the BESS component	In-depth performances battery modelling based on electrical equivalent-circuit equations (EC_model)
Simulation time-step	Time-step of 1 mn
Control algorithms	Advanced control algorithms (including GAMS optimization)
Forecast quality	A standard PV forecast is used

Table 7: BESS application#1 - Reference scenario

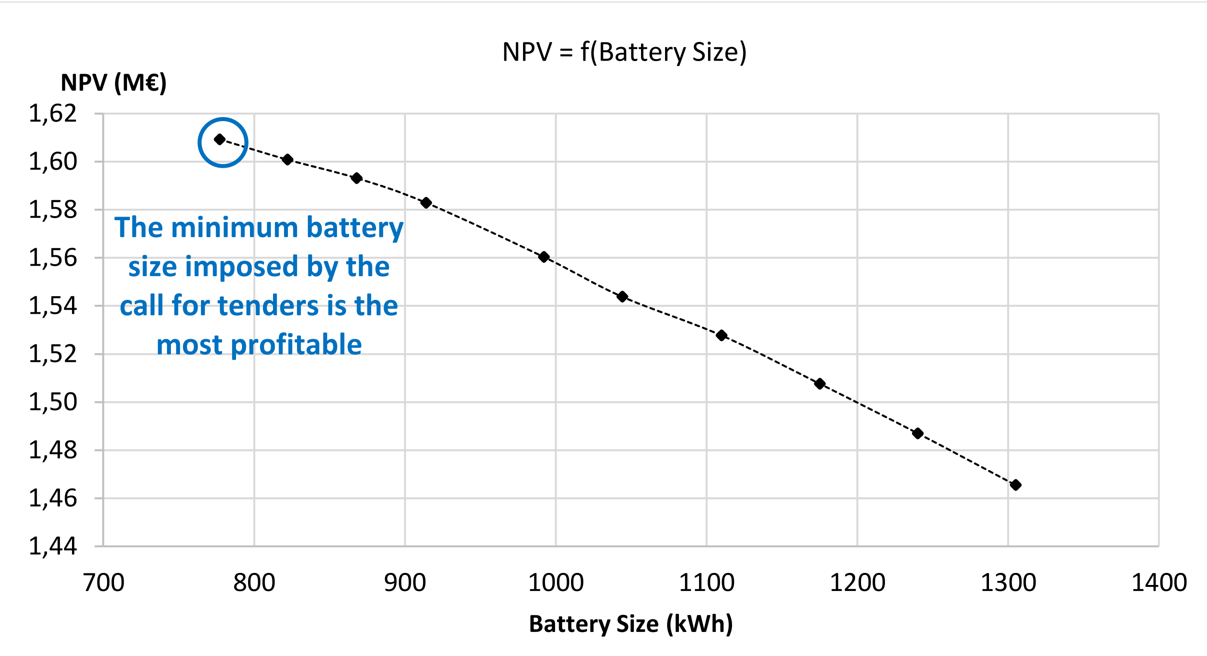


Figure 10: BESS application#1 – Optimal sizing reference curve

Figure 10 shows that the evolution of the sizing indicator as a function of the BESS size has not an optimum curve shape, but is rather quite linear, with the minimum battery size imposed being the most profitable configuration. It can indeed be demonstrated that, because of the economic framework defined by the call of tenders, **additional battery capacity costs are always higher than the additional incomes generated by a larger storage system**.

As the optimal size is always the smallest for this application, this will unfortunately prevent the sensitivity study from identifying when an influencing factor has an impact strong enough to change the value of the optimal size. Nevertheless the impact on the sizing criteria (Net Present Value) could be quantified.

4.2 BESS application #2: hybrid microgrid

4.2.1 Application description

The second application is related to a standalone hybrid microgrid, which is composed of a load to supply for the demand (industrial power profile), and of a diesel generator with the addition of solar PV for the generation, as represented on Figure 11.

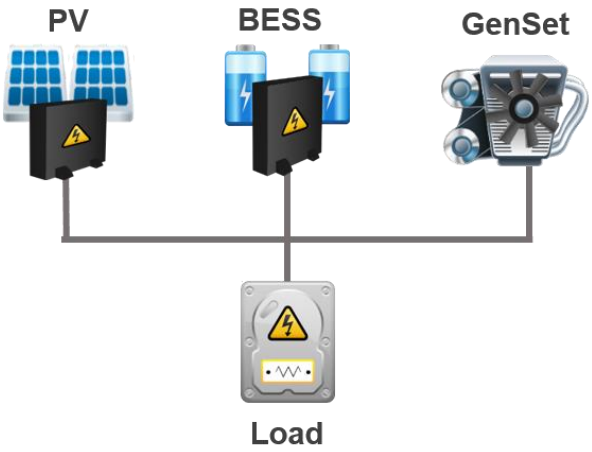


Figure 11: BESS application#2 - Hybrid microgrid topology

This use case is typical of remote areas where electricity consumption is too low to justify the investment to connect them to the main grid. In the past, fossil fuel generators such as diesel generators have been heavily used for power supply in those areas. However, the rising cost of fuel for the generators, the decreasing cost of renewable energy technologies, as well as the environmental concerns, has led to standalone hybrid energy systems as an attractive solution for remote area power supply.

Standalone hybrid energy systems generally include single or various kinds of non-renewable and renewable energy resources, e.g., diesel generators, solar PV, wind turbines or others. All standalone hybrid systems require a form of back-up power supply to ensure reliability and continuity of supply. In most cases, this is supplied by either a diesel generator or some form of energy storage system.

The key objective of employing a BESS in a standalone hybrid system is to match the imbalance between renewable energy generation and electricity demand to ensure continuity of power supply. In this sense, the functions of diesel generators can be partially or completely replaced by renewable energy and BESS.

4.2.2 Scenario configuration

The simulation scenario has been set up in accordance with a real standalone application in Africa, where an industrial load of approximatively 40 kW peak power is supplied by means of a 100 kVA diesel generator and a 130 kW PV Plant. The main purpose of the BESS is to reduce the fuel consumption by storing the excess of electricity produced by the PV Plant and delivering it later to the load, thus minimizing the use of the diesel generator.

As the imbalance between generation and demand can be managed by the BESS, it becomes also possible to use the diesel generator only at its best yield operating regime, which also contributes to optimize the fuel consumption. Details about component configuration are given in Table 8.

Load	Peak power	40 kW
	Load profile	weekly consumption profile : 1 year data input obtained from some full-week power measurement samples randomly duplicated
Diesel generator	Rated power (PRP)	100 kVA / 80 kWe
	Fuel consumption	Consumption @ 110% load (L/h) 25.50 Consumption @ 100% load (L/h) 23.50 Consumption @ 75% load (L/h) 16.50 Consumption @ 50% load (L/h) 11.50 Consumption @ 5% load (L/h) 3.50
PV Plant	Installed capacity (peak power)	130 kWp
	PV degradation rate	0.5% per year
	PV producible dataset	1 year measurement data from a monitored PV plant in Corsica
	PV forecast dataset	1 year historical irradiance forecasts of the Corsica plant location
BESS	Battery technology	Li-ion / app. 6.5 kWh per battery module
	Depth of discharge	90% (from $SOC_{min} = 5\%$ to $SOC_{max} = 95\%$)
	Battery replacement	Replacement when SOH is 70%
	Battery capacity	From app. 110 kWh up to app. 1100 kWh / 10 size configurations made of series/parallel modules assembly in coherence with converter DC voltage range
	DC/AC converter power	Up to 200 kVA

Table 8: BESS application#2 - System components setup

4.2.3 Simulation of operation

A graphical verification of the correct behaviour of the simulation could be done on the same 3-days sequence as the first illustrative application (section 4.1.3), as represented on Figure 12.

The control strategy implemented for this illustration is a basic control, which consists in using SOC thresholds to start and stop the diesel generator:

- The fuel generator is started when BESS SOC < 10%, i.e. when battery is almost empty,
- The fuel generator is stopped when BESS SOC > 30%.

As expected, the less PV production there is, the more frequently the fuel generator must be launched in order to supply the load and recharge the battery.

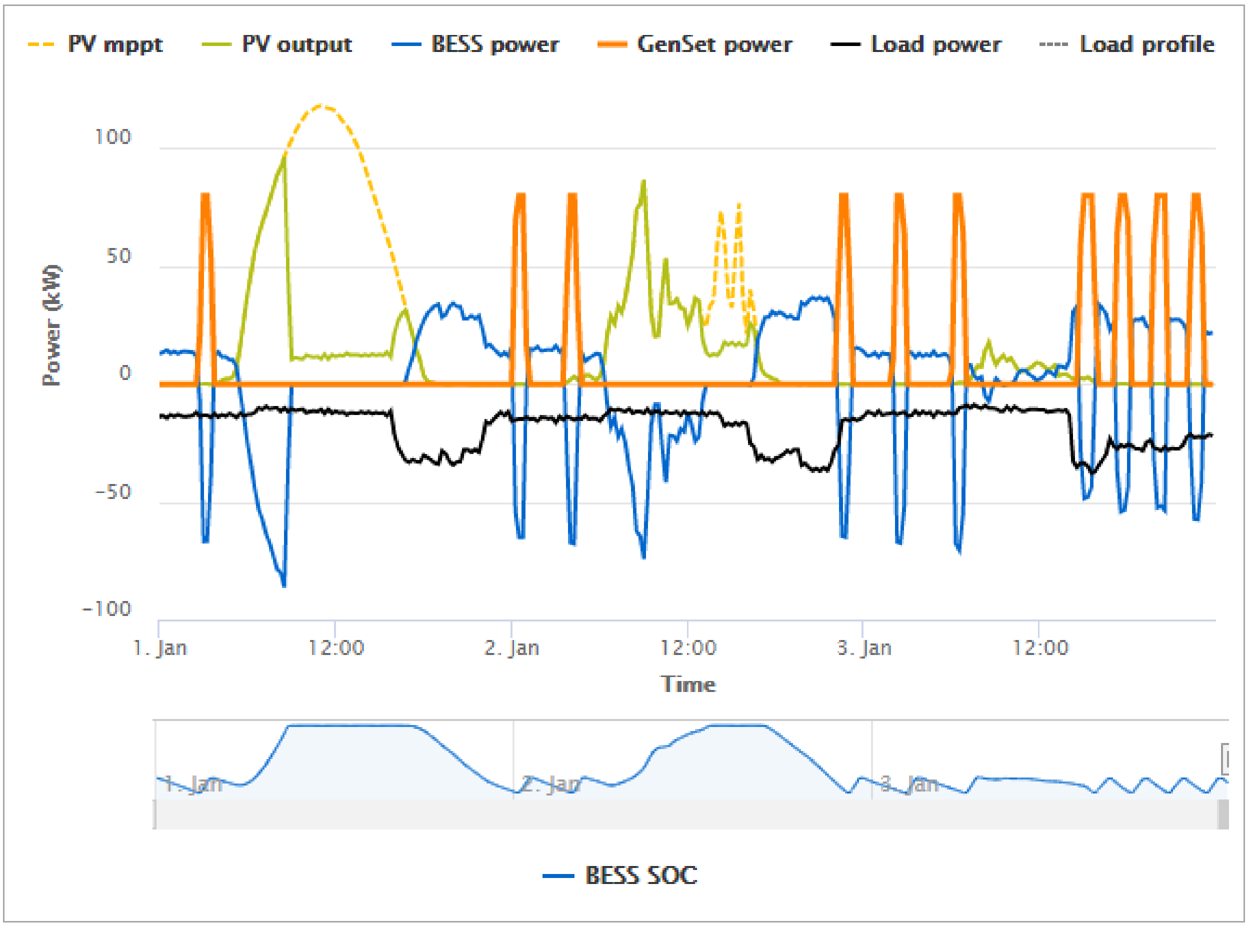


Figure 12: BESS application#2 – Illustration of simulated operation

4.2.4 BESS sizing criteria

For this standalone application case, **LCOE is a well suited sizing indicator** as it will enable to estimate the average cost of the energy produced to supply the industrial load. The optimal BESS size will be determined by the configuration for which the LCOE is the lowest.

Regarding the LCOE formula (reminded in Equation 2 below):

- The total initial capital investment for producing electricity - including PV plant, fuel generator and BESS procurement and installation – is accounted at year 0 ($CAPEX_0$),
- For each following year, the operation costs will be summed, including all maintenance costs, fuel costs, and replacement costs when necessary,
- In the denominator, the accounted energy is only the useful energy, i.e. the final electricity consumed by the load.

Levelized Cost of Energy Determine the average net present cost of electricity generation over the project lifetime	$$\boldsymbol{LCOE} = \frac{\sum_{n=0}^{N} \frac{CAPEX_n + OPEX_n}{(1+r)^n}}{\sum_{n=0}^{N} \frac{E_n}{(1+r)^n}}$$	$CAPEX_n$: total investment costs of year n $OPEX_n$: total O&M costs of year n E_n : total electricity consumed by the load in the year n r : discount rate N : project lifetime

Equation 2: BESS application#2 - LCOE indicator used as optimal sizing criteria

The set of economic assumptions used to compute the LCOE indicator are listed in Table 9. They are based on several recent economic studies [47] [48] [49] [50] [51] about PV and storage.

Category	Designation	Value
Project	Project lifetime	20 years
	Discount rate	5 %
Initial investment	PV plant	825 € / kWp
	ESS battery & auxiliaries	350 € / kWh
	ESS converter & auxiliaries	200 € / kW
	Diesel generator	500 € / kW
Operation costs	PV plant	Per year, 3% of initial investment
	ESS battery	Per year, 3% of initial investment
	ESS converter	Per year, 3% of initial investment
	Fuel cost	0.8 € / L

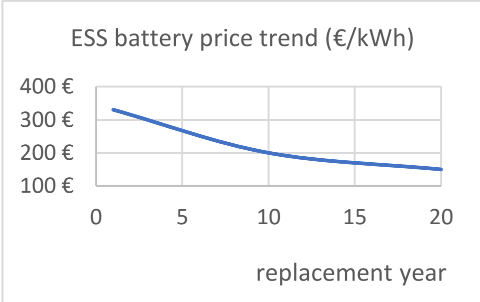
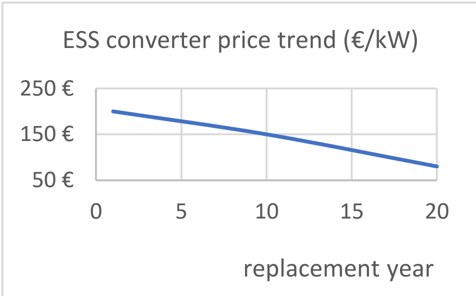
Category	Designation	Value
	O&M cost per hour of diesel generator operation (excluding fuel consumption)	3 €
	Diesel generator startup cost	6 € (2h of operation)
Replacement costs	ESS battery lifespan	Until SOH reaches 70%
	ESS battery replacement cost	Decrease trend over the 20 next years 
	ESS converter lifespan	10 years
	Diesel generator lifespan	20 000 operation hours
	ESS converter replacement cost	Decrease trend over the 20 next years 

Table 9: BESS application#2 - Economic assumptions

4.2.5 Optimal sizing reference curve

The LCOE values obtained along the BESS sizes range explored through the simulation for the reference scenario are represented on Figure 13. The reference scenario for this application case is summarized in Table 10.

Influencing factor	Reference scenario
Precision of the BESS efficiency behaviour	BESS model parameters include tables of precise efficiency values varying according to temperature, current and SOC
Degradation of battery capacity due to ageing	BESS model parameters include ageing data enabling the simulation to take into account the battery capacity degradation over time

Influencing factor	Reference scenario
technical modelling of the BESS component	In-depth performances battery modelling based on electrical equivalent-circuit equations (EC_model)
Simulation time-step	Time-step of 1 mn
control algorithms	Basic control algorithms (Genset start and stop on BESS SOC thresholds)
Forecast quality	A standard PV forecast is used

Table 10: BESS application#2 - Reference scenario

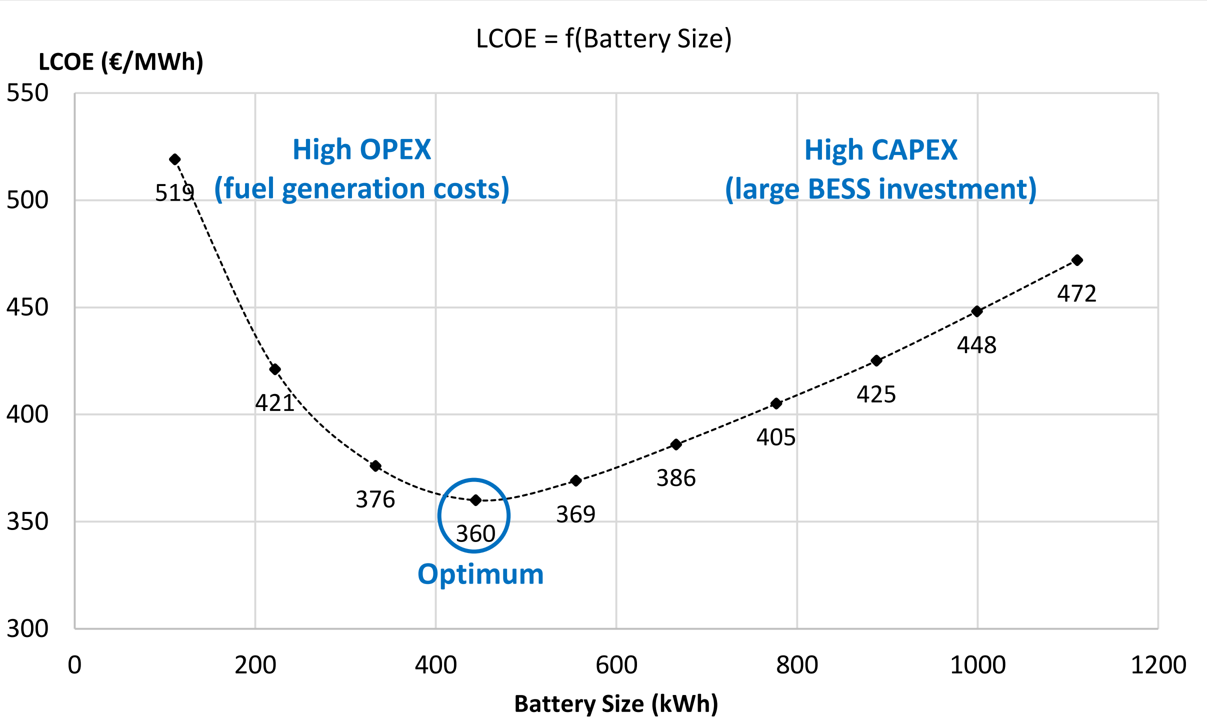


Figure 13: BESS application#2 – Optimal sizing baseline

For this application case, the evolution of LCOE as a function of the BESS size reveals an optimum curve shape, as shown on Figure 13. The high LCOE for the smallest BESS configurations [100 – 300 kWh] is mainly composed of OPEX costs, due to the intense use of the fuel generator, and few CAPEX. On the opposite side, the LCOE for the largest BESS configurations [> 700 kWh] contains a strong proportion of CAPEX due to the high initial investment for the storage system procurement, and low fuel costs. Between the two ends of the curve, the optimal trade-off between BESS investment cost and fuel consumption reduction is obtained for a battery size of 440 kWh with the lowest LCOE value, here at 360€/MWh.

5 Sensitivity analysis results

The following subsections describe the comparison results obtained for each of the influencing factor investigated through the sensitivity study, according to the scope detailed in section 3.2.

As the **conclusions are mostly similar for the 2 illustrative application cases**, **BESS application #2** related to hybrid microgrid has been **chosen** to exhaustively inspect the detailed results, since its **optimum shaped curve is more suited to the graphic visualisation of impacts**.

In case of different conclusions found for BESS application #1, this is explicitly mentioned at the end of the relevant subsection.

5.1 Influence of BESS efficiency precision

The energy efficiency of a storage system is obviously one of the major characteristics impacting the performance of an application. This efficiency may be modelled in different manners for the BESS component simulation, either through a simple constant value or through some more complex equations aiming at reproducing more precisely the dynamic behaviour of the system.

5.1.1 Variable versus constant efficiency parameters setup

The purpose of this section is to compare the optimal sizing results between modelling BESS behaviour with a precise variable efficiency dataset and using a constant average efficiency single value.

As introduced in section 3.1.1.2, the in-depth BESS model based on electrical equivalent-circuit (EC_model) enables to use large sets of electrical data values to reproduce as precisely as possible the operation of the storage system. These data tables, in particular composed of battery open circuit voltage and internal resistance values measured under various conditions of current, temperature or state-of-charge, lead to define some variable efficiency, which instantaneous value depends on the instantaneous state of the system. Based on the specific data electrical values related to the Li-ion battery and DC/AC converter products chosen for the two illustrative application cases of the present study, Figure 14 illustrates the resulting efficiency curves as a function of the power setpoint applied to the system: from battery and converter individual efficiency curves, the overall BESS efficiency can then be deduced.

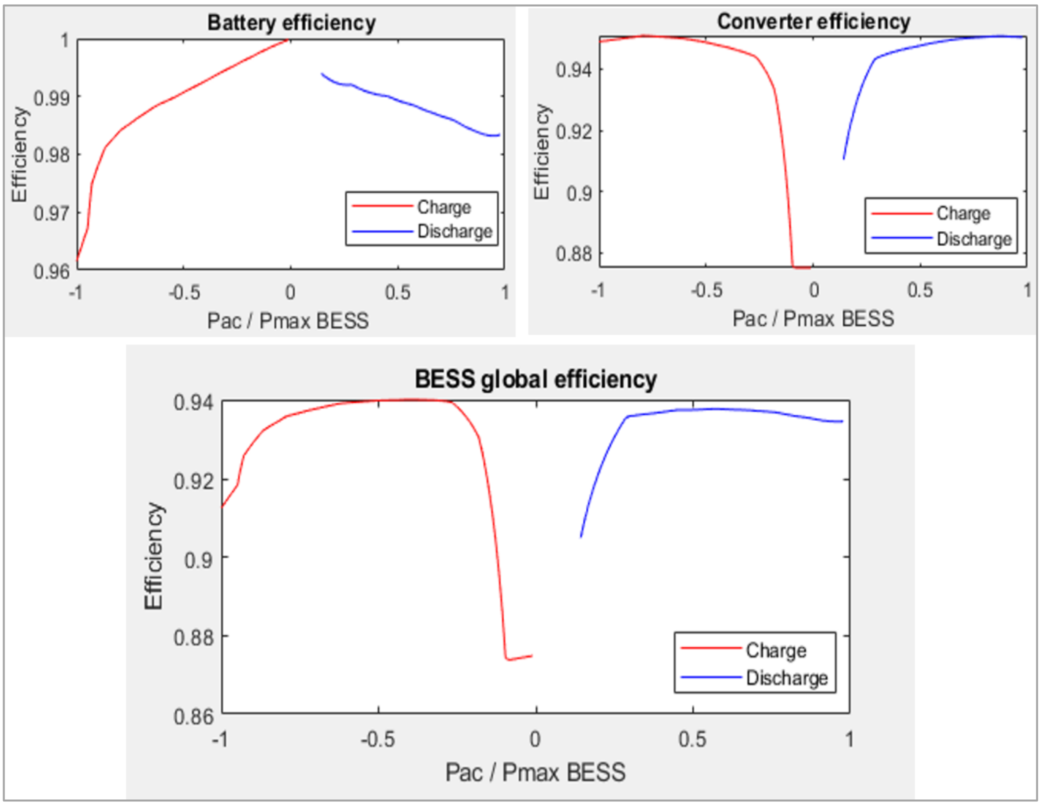


Figure 14: BESS variable efficiency curves

To evaluate the influence on optimal sizing of variable versus constant efficiency, the baseline scenario uses the EC_model with the original parameters dataset, whereas the comparative scenario uses a different parameters dataset where all electrical values such as battery OCV and internal resistances have been set to their average value, leading thus to an average constant efficiency. All other parameters remain identical between the 2 scenarios, with their values set to the reference scenario.

Precision of the BESS efficiency behaviour	*Baseline*	BESS model parameters include tables of precise efficiency values varying according to temperature, current and SOC
	Comparative	BESS efficiency is set up as a constant value (average efficiency)

Table 11: Face to face scenarios for variable/constant efficiency comparison

Figure 15 below superimposes the two LCOE curves obtained respectively with the baseline and the comparative scenarios for the BESS application #2 (hybrid microgrid). With a negligible average deviation of 0.25%, the LCOE values obtained with the constant efficiency are identical to those obtained through the baseline, meaning that the optimal sizing process leads to the same result either with a complex dataset of variable efficiency values or with a single constant efficiency value. Same conclusion has been observed with BESS application #1. From a statistical point of view, this is a logical conclusion: over a 20 years period operation simulation, the various efficiency operating states of the BESS follow a normal distribution and are equally dispersed around the average efficiency value.

This proof result suggests the possible use of simplified BESS models in the optimal sizing process, where BESS efficiency parameter can be set as a constant single value, without risk on the optimal size determination. The benefits of using simplified models at the design stage are related both to the computational time reduction, as well as being able to overcome limited modelling skills or difficult access for the system designer to a large range of battery parameters. This subject will be further discussed in section 5.3 related to the sensitivity of BESS optimal sizing to the degree of technical modelling.

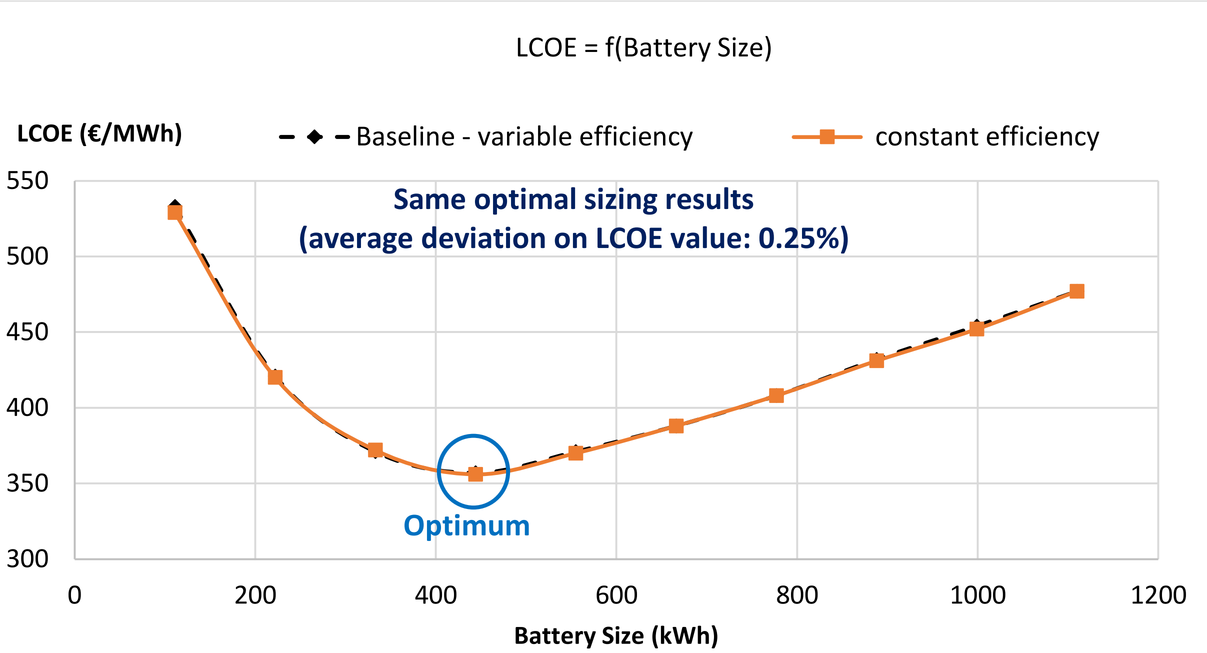


Figure 15: Graphic comparison between variable and constant efficiency results

5.1.2 Constant efficiency value approximation

The previous section has demonstrated that BESS variable efficiency parameters can be replaced by the BESS average efficiency value without any difference in the optimal sizing results. This assumes that **sufficient technical data related to the BESS enables to accurately estimate its average efficiency**. If this is not the case, a rough approximation of the BESS global efficiency can lead to use an efficiency value parameter which may differ from the real equipment performance by a few percent. The sensitivity of the sizing indicator to the efficiency value setting is graphically represented on Figure 16 and Figure 17 below. Figure 16 illustrates the impact of different constant efficiency values setting on the LCOE curves used for optimal size determination. While the actual average efficiency is 91% (orange curve), the efficiency settings to 85% and 95% lead to large deviations from the reference curve. As the general shape of the LCOE curve is nevertheless preserved, the optimal BESS size remains the same (440 kWh), but with a noticeable difference on the corresponding LCOE value. Figure 17 gives a quantification of the error made on the LCOE as a function of the efficiency value deviation. It emerges from this graphic that when the value of the sizing indicator has an importance for the project study, the **average efficiency of the BESS must be carefully estimated**, as an approximation error of 5% on the efficiency value (for example rounding 0.95 to 0.9) causes a difference of about 4% on the LCOE value.

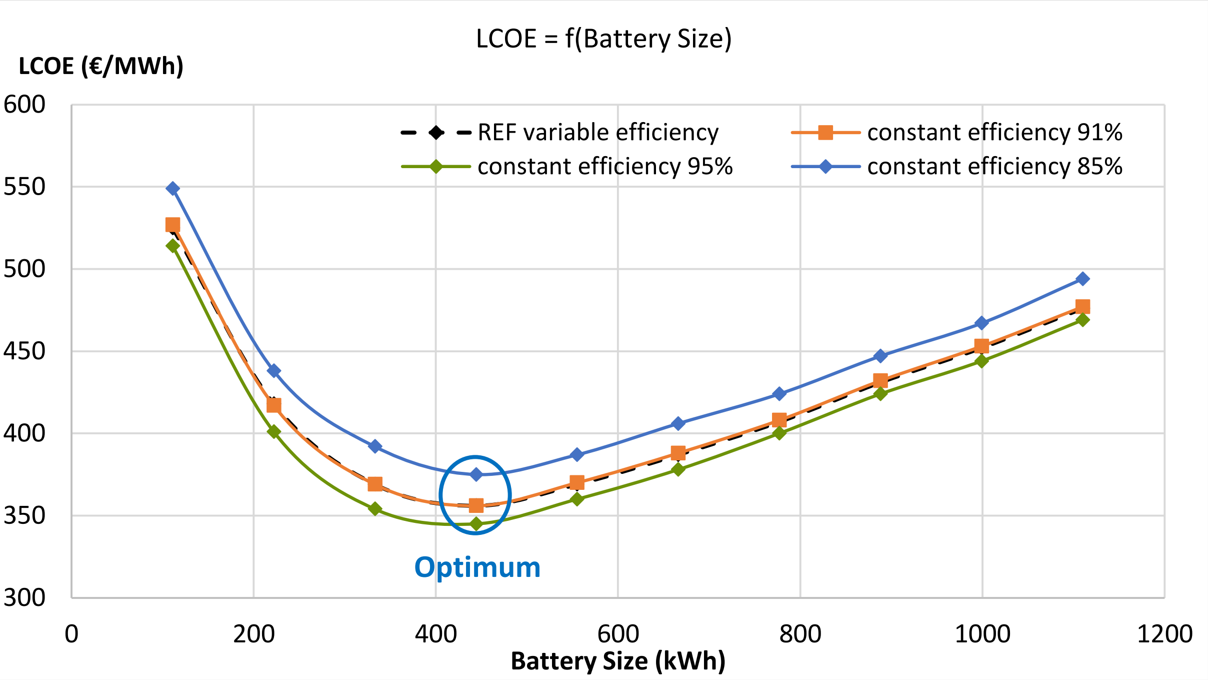


Figure 16: Impact on sizing indicator of different BESS efficiency settings

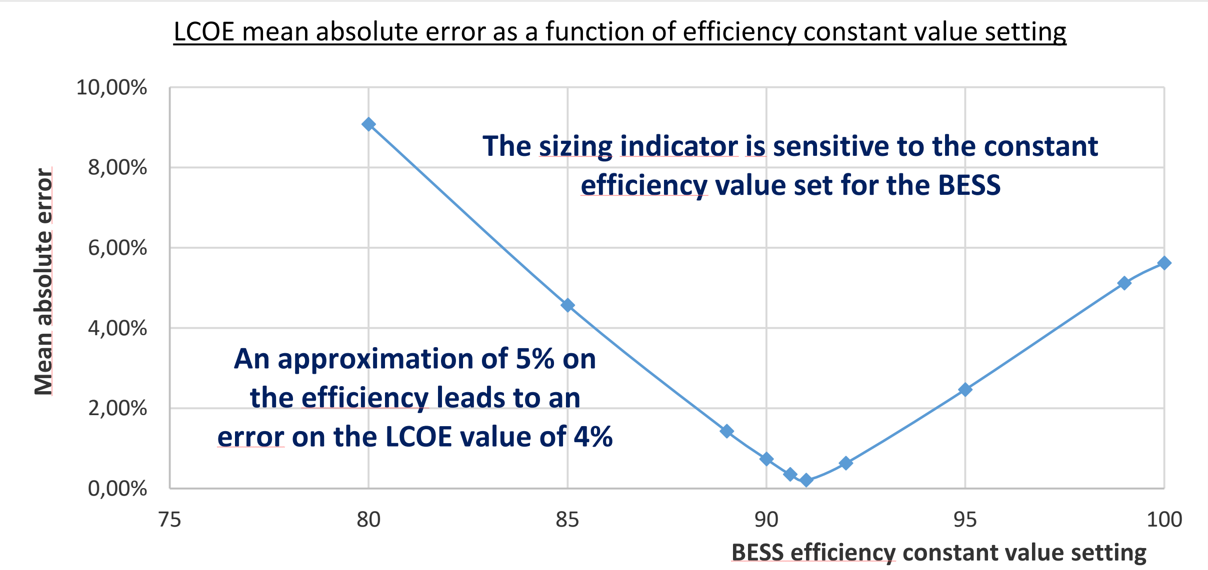


Figure 17: LCOE mean absolute error along BESS efficiency approximation

5.2 Influence of taking ageing into account

Batteries as energy storage systems have a drawback in that they degrade with charge/discharge cycling and over time. For Li-ion batteries, this degradation mainly causes a decrease of the usable capacity of the battery. The ageing process of electrochemical battery is commonly divided into two contributions: calendar and cycling ageing. Calendar ageing of battery is mostly due to formation of passivation layer on negative electrodes over time, which degrades battery even when it is just stored. Cycling ageing corresponds to the battery degradation due to its operation which is affected by the number of charge discharge cycles and strongly depends on the conditions under which the battery is operated, such as temperature, charging/discharging rate, and depth of discharge (DoD).

A precise modelling of the battery ageing for optimal sizing purpose may be a difficult challenge, as it involves complex equations and requires a lot of data which are rarely available, even from battery manufacturers. The influence of battery ageing on optimal sizing can nevertheless be important since the capacity decrease over the project lifetime may be significant.

5.2.1 Impact on optimal sizing of battery capacity degradation

To assess the impact on optimal sizing of taking into account the battery capacity degradation over time, the study benefits from a state of health (SOH) computation module which is integrated into the EC_model. This module enables to precisely estimate the battery capacity degradation at each simulation step from ageing lab-extracted parameters specific to the Li-ion chemistry of the battery selected for the illustrative application cases. It forms the baseline for the comparison analysis. The comparative scenario is obtained by neutralizing all ageing parameters, thus leading to a battery capacity which remains constant over time. All other settings are identical between the 2 scenarios (corresponding to the reference scenario). It is worth mentioning in particular that the replacement costs of the battery are computed to the same value in the 2 scenarios even if SOH value is artificially maintained as constant in the comparative scenario. In this way, the comparison is only focused on taking into account the technical impact due to the decrease of the useful battery capacity over time.

Degradation of battery capacity due to ageing	*Baseline*	BESS model parameters include ageing data enabling the simulation to take into account the battery capacity degradation over time
	Comparative	Battery capacity remains constant over time

Table 12: Face to face scenarios for capacity degradation comparison

Figure 18 illustrates the impact of taking into account the battery capacity degradation due to ageing in the optimal sizing procedure. Naturally, the LCOE is slightly higher when the degradation of BESS performances over time is taken into account. The impact is much stronger on the left side of the graph: for the smallest BESS configurations [100 – 400 kWh] the LCOE is mainly composed of OPEX fuel costs, which are even higher when the battery capacity decreases. On the opposite side, the LCOE for the largest BESS configurations is mainly composed of CAPEX for initial investment, which is not affected by the change of scenario. Even if the optimal size (440kWh) will not be changed between these 2 scenarios for this application case, the important gap induced on the sizing indicator around the optimal configuration leads to be cautious and tends to demonstrate the **importance of taking ageing into account**: As shown in Table 13, the **difference on the LCOE** value for the optimal configuration is about 4.5% and increases between 5 and 10% for the smallest BESS configurations.

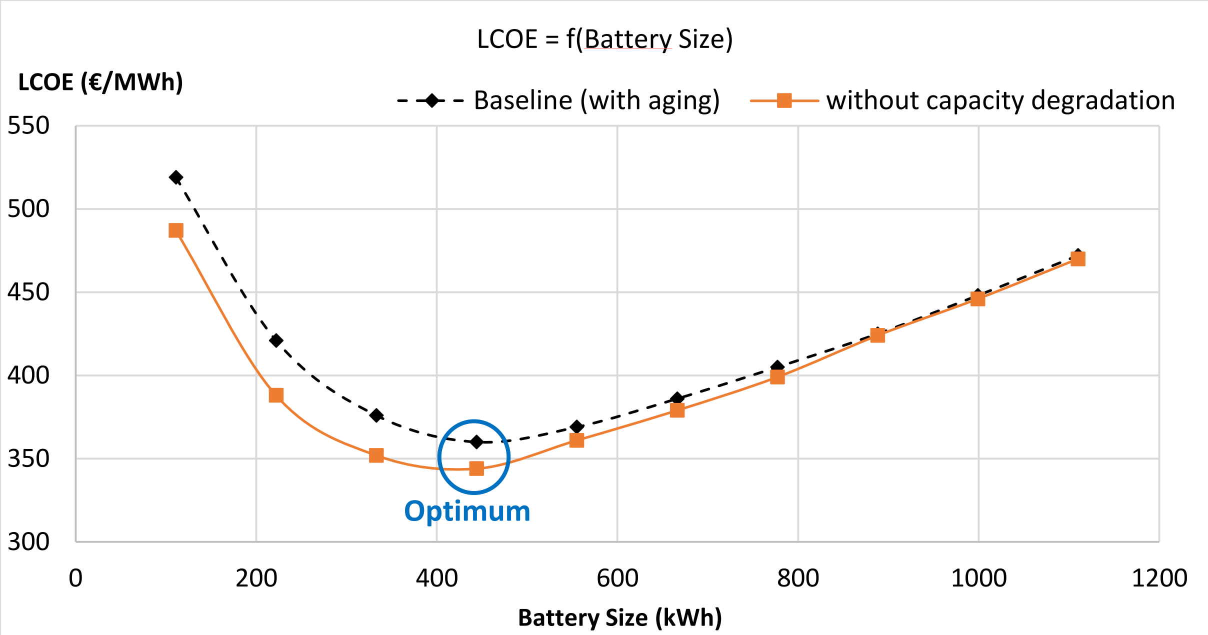


Figure 18: Impact on sizing indicator of taking into account battery capacity degradation

	Baseline scenario - Ageing taken into account	Comparative scenario - Without capacity degradation	
BESS size (kWh)	**LCOE (€/MWh)**	**LCOE (€/MWh)**	**Relative error**
111	**519**	487	**6,17%**
222	**421**	388	**7,84%**
333	**376**	352	**6,38%**
444	**360**	344	**4,44%**
555	**369**	361	**2,17%**
666	**386**	379	1,81%
777	**405**	399	1,48%
888	**425**	424	0,24%
999	**448**	446	0,45%
1110	**472**	470	0,42%
		Mean error	**3,14%**

Table 13: LCOE values comparison for capacity degradation impact

5.2.2 Approximation with constant but moderately degraded capacity

In case of limited availability of accurate battery ageing data, a possible rough way of taking into account the capacity degradation over time in the optimal sizing procedure could be to run simulations with a constant but moderately degraded capacity. The manufacturer of the Li-ion battery simulated for the illustrative application cases recommends replacing the battery when its remaining useful capacity corresponds to 70% of its initial capacity, meaning the end of life of the battery at SOH=70%. An average degraded capacity thus corresponds to SOH=85%. The simulations launched with a constant battery capacity of 85% of the nominal capacity lead to an excellent approximation of the LCOE values obtained with the baseline, as shown on Figure 19 (green curve), with an average relative error around 0.5%. However, the **average degraded capacity seems to be a relevant value in this case of figure only for specific reasons**, such as the duration of the project (20 years) which is long enough for the battery to have some complete life cycles. There is no doubt that this method requires to adapt the constant degraded capacity to the application characteristics, which does not seem obvious to do. If the average degraded capacity is not set to the correct value, there is still a risk to approximate LCOE values with several percent of error, as illustrated by the purple curve on Figure 19 where constant degraded capacity has been set to 90%.

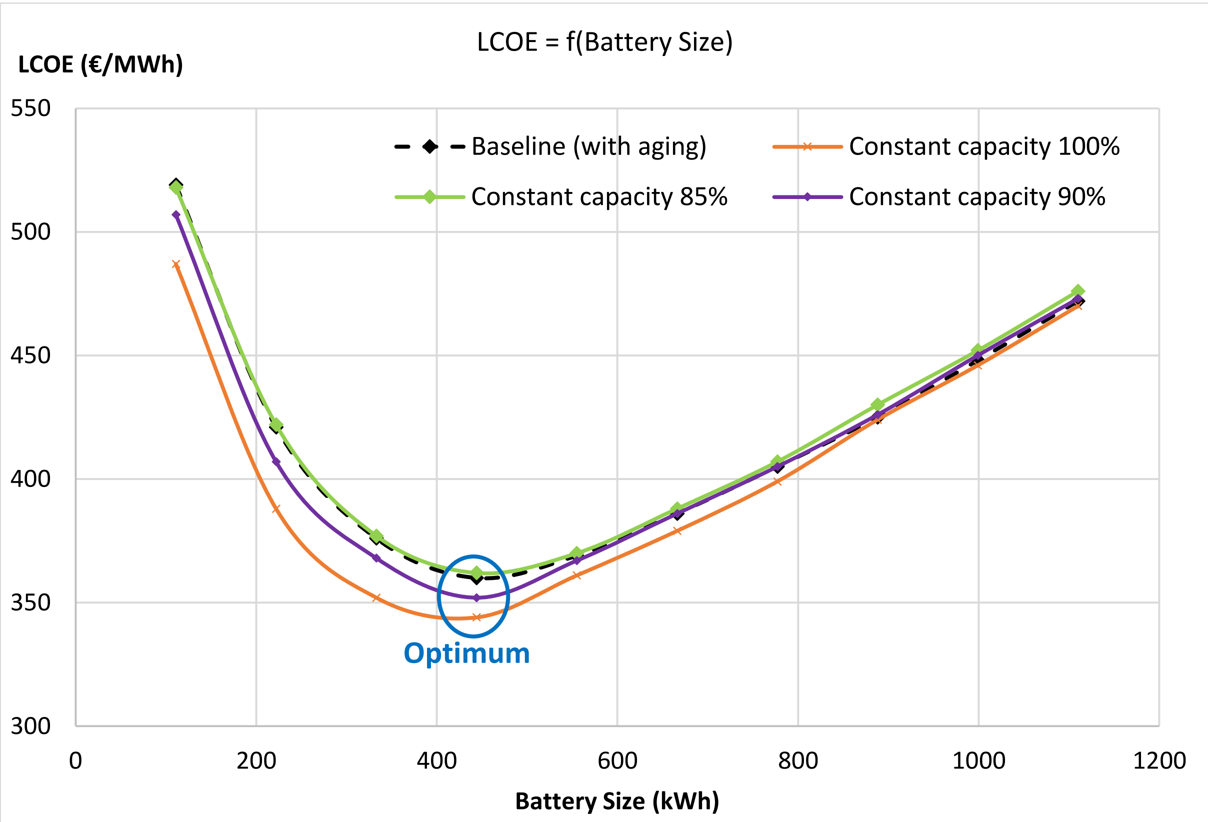


Figure 19: Approximation of ageing impact through constant degraded capacity

	Baseline scenario - Ageing taken into account	Comparative scenario - Constant capacity 85%		Comparative scenario - Constant capacity 90%	
BESS size (kWh)	LCOE (€/MWh)	LCOE (€/MWh)	Relative error	LCOE (€/MWh)	Relative error
111	**519**	**518**	0,19%	**507**	2,31%
222	**421**	**422**	0,24%	**407**	3,33%
333	**376**	**377**	0,27%	**368**	2,13%
444	**360**	**362**	0,56%	**352**	2,22%
555	**369**	**370**	0,27%	**367**	0,54%
666	**386**	**388**	0,52%	**386**	0,00%
777	**405**	**407**	0,49%	**405**	0,00%
888	**425**	**430**	1,18%	**426**	0,24%
999	**448**	**452**	0,89%	**450**	0,45%
1110	**472**	**476**	0,85%	**473**	0,21%
		Mean error	**0,55%**	**Mean error**	**1,14%**

Table 14: LCOE values obtained through constant degraded capacity

5.2.3 Approximation with macro ageing data

When precise ageing measurements data and/or dynamic ageing model are not available, another possibility is to use overall battery lifetime information given on the technical datasheets from the manufacturer. General trends on calendar ageing and cycling ageing contributions to the battery degradation can be used to perform some global estimation of the SOH indicator. In our case study, the datasheets of the li-ion battery contains some tables estimating the number of cycles the battery could performed in its life as well as calendar ageing general trend. By implementing in post-processing an equation giving the SOH as a function of the year and the number of cycles, it was therefore **possible to get a yearly estimation of the battery capacity degradation** without using the continuous ageing modelling module over a 20 year simulation. With this kind of “macro modelling” directly **implemented in the post-processing calculations**, it is even possible to limit the simulation at a single year period and then to use the indicators obtained in first year to extrapolate all annual key indicators for the 19 following years, as long as the application case characteristics enable to find some linearization or approximation rules which allow to iteratively deduce all annual incomes and costs from one year to the next. For the hybrid microgrid application case, it is for example possible to express the increase of the fuel generator operation costs as a function of the decrease of the battery capacity, enabling in thus to **set an extrapolation method** which deduces from the 1st year simulation results all the indicators that are required for the LCOE computation over the 20 years of the project lifetime. The LCOE results obtained through this extrapolation method using macro ageing data are depicted on Figure 20. The accuracy is entirely acceptable, with an average absolute error around one percent, but above all the **gain in computational time is considerable**: with a simulation over a single year instead of 20 years, the LCOE calculation benefits from a time reduction factor of 20, as shown in Table 15.

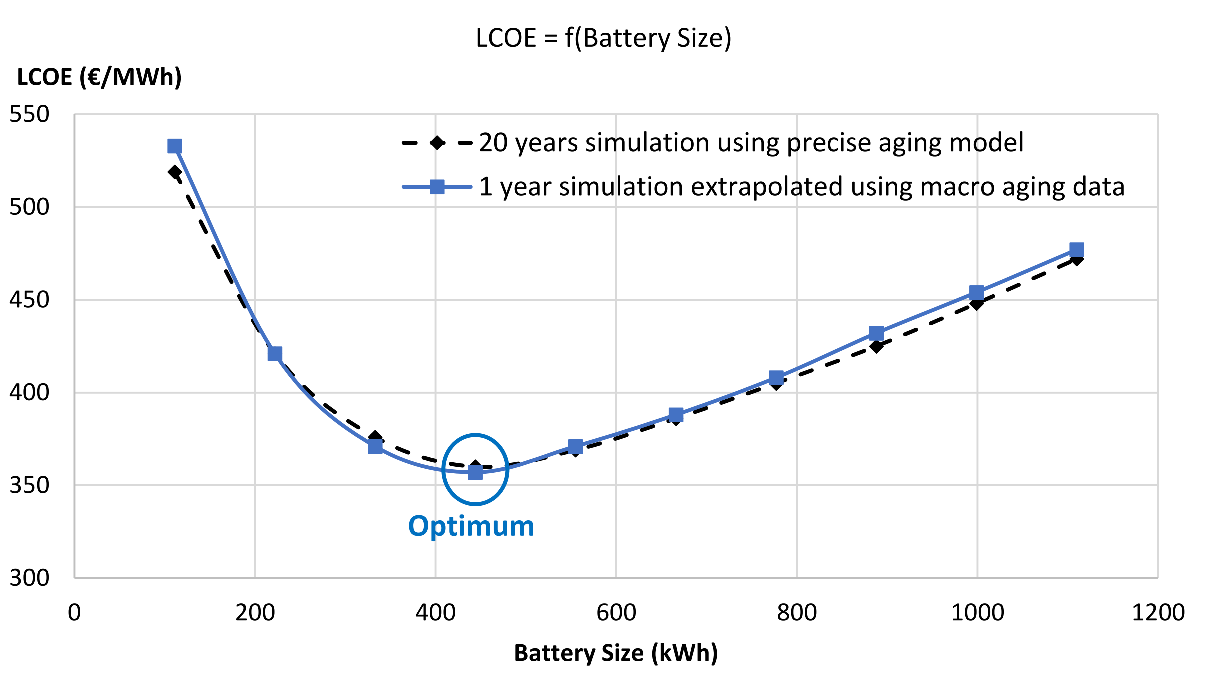


Figure 20: Approximation of LCOE values through extrapolation of a one-year simulation

	Baseline scenario - 20y simulation using precise ageing model	Comparative scenario - 1y simulation extrapolated using macro ageing data	
BESS size (kWh)	**LCOE (€/MWh)**	**LCOE (€/MWh)**	**Relative error**
111	**519**	533	2,70%
222	**421**	421	0,00%
333	**376**	371	1,33%
444	**360**	357	0,83%
555	**369**	371	0,54%
666	**386**	388	0,52%
777	**405**	408	0,74%
888	**425**	432	1,65%
999	**448**	454	1,34%
1110	**472**	477	1,06%
		Mean error	**1,07%**
Computation time / config	hh:mm:ss **01:10:00**	hh:mm:ss **00:03:30**	time reduction factor **20**

Table 15: LCOE values obtained through extrapolation from 1 year simulation results using macro ageing data

To sum up this section about the battery performances degradation over time, taking into account the impact of ageing in optimal sizing procedure is something necessary. The advantages and disadvantages of the different techniques used in this study to estimate this degradation are summarised in Table 16.

Ageing estimation method	Pros	Cons
SOH computation integrated into BESS model: battery performances degradation is calculated at each simulation time-step	• Results are the most precise	• In-depth ageing parameter values difficult to collect • Ageing modelling requires expert skills • Computational extensive time required for simulation
Simulation with constant but moderately degraded battery performances over the project lifetime	• Ease of implementation	• It may be difficult to find the appropriate average constant degraded capacity value in regards to the application and battery technology specificities
Yearly estimates of performances degradation through the use of macro ageing data in post-processing calculations	• Rough ageing estimates more easy to obtain than detailed lab-extracted data • Faster calculations (degradation is only estimated once a year)	• Possible loss of precision on sizing indicator results, depending on the reliability of the macro ageing estimates

Table 16: Summary of the pros and cons of the methods used to take ageing into account in the BESS optimal size determination

5.3 Influence of degree of technical modelling

Now that it has been proven that BESS variable efficiency behaviour has no influence on optimal sizing and that some workarounds can be achieved to estimate the battery degradation impact without using a detailed ageing model in simulation, the interest of using an in-depth performances BESS model is considerably reduced. An electrical equivalent-circuit model (EC_model) has been used so far in the simulation processing: its equations precisely reproduce the electrical behaviour of the BESS component. However, one drawback of using such a model is that it requires a very large number of parameters composed of electrical values like battery open voltage and internal resistance measurements under various conditions of temperature, SOC and current, both for charging and discharging sequences. Firstly, these detailed data may be difficult to obtain from the manufacturer or may require a long period of characterization in laboratory. Secondly, they induce a significant computation time in simulation because the resolution of the various electrical equations involves carrying out several interpolations among numerous lookup tables at each time step. **As average efficiency value or yearly estimates for ageing are sufficient to perform accurate optimal size determination**, a simplified model of the BESS may be convenient and lead to ease the implementation as well as significantly decrease the overall calculation time.

To perform this comparison, LCOE values previously obtained through the use of the EC_model have been challenged with those obtained when using a simplified BESS model, here denoted as E/P_model. In contrast with the EC_model, the E/P_model doesn't compute any detailed electrical equations such as battery current and voltage level but directly handles power and energy quantities from global efficiency parameter settings. Consequently, the parameter dataset is much less detailed in the case of the E/P_model and is mainly limited to the overall efficiency values of the whole system, which can either be set to a single value. For our case of figure, a constant BESS efficiency value of 91% has been set. Furthermore, the E/P_model doesn't perform any SOH computations. As a consequence, **taking ageing into account for optimal sizing should be done either by setting an initial degraded capacity value or by estimating the capacity degradation from macro data in post-processing calculations**. These two possibilities have been explored in the results illustrated on Figure 21. Both scenarios with E/P_model lead to very close results and give an accurate estimation of the indicator reference values computed in the baseline scenario, with an average absolute error around one percent. The second comparative scenario, using the extrapolation method over a single year period, is however much more advantageous in terms of computational time: as stated in Table 18, the optimal size determination is 140 times faster with this scenario than with the 20 years simulations involving the EC_model.

Degree of technical modelling of the BESS component	*Baseline*	In-depth performances battery modelling based on equivalent-circuit equations (EC_model)
	Comparative	Simplified modelling of the energy/power behaviour of the BESS (E/P_model)

Table 17: Face to face scenarios for simulation time step comparison

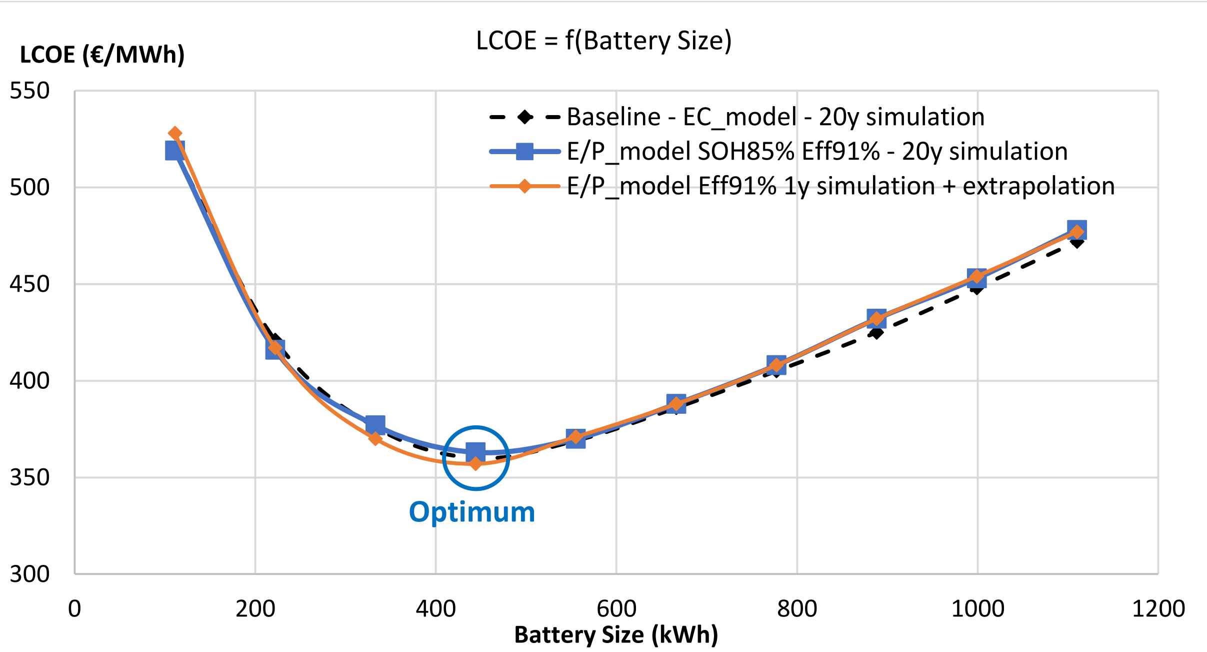


Figure 21: Impact on sizing indicator of using simplified BESS model

	EC model dyn. ageing variable eff. 20y simu	E/P model cst SOH 85% cst eff. 91% 20y simu		E/P model cst eff.91% 1y simu + extrapolation	
BESS size (kWh)	LCOE (€/MWh)	LCOE (€/MWh)	Relative error	LCOE (€/MWh)	Relative error
111	**519**	519	0,00%	528	1,73%
222	**421**	416	1,19%	417	0,95%
333	**376**	377	0,27%	370	1,60%
444	**360**	363	0,83%	357	0,83%
555	**369**	370	0,27%	371	0,54%
666	**386**	388	0,52%	388	0,52%
777	**405**	408	0,74%	408	0,74%
888	**425**	432	1,65%	432	1,65%
999	**448**	453	1,12%	454	1,34%
1110	**472**	478	1,27%	477	1,06%
		Mean error	**0,79%**	**Mean error**	**1,10%**
Computation time / config	hh:mm:ss **01:10:00**	hh:mm:ss **00:10:00**	time reduction factor **7**	hh:mm:ss **00:00:30**	time reduction factor **140**

Table 18: Detailed results obtained through different BESS models

5.4 Influence of simulation time step

Techno-economic analyses are usually performed on a simulation time step of one hour without much justification on the suitability of such a choice. Increasing the time step has obviously an immediate benefit as it will reduce the required overall computation time (for a single simulation and by extension for the entire optimization process). However, we may wonder what could be the impact of using different simulation time steps on the overall optimal BESS sizing.

The baseline used as the reference in this section corresponds to the last scenario implemented in previous section, i.e. the extrapolation method over a single year simulation involving the BESS simplified model. These baseline results obtained through a simulation time step of 1 minute are compared with the results obtained by running the same simulations with a time step value of respectively 10 minutes and 1 hour.

Simulation time-step	*Baseline*	Time-step of 1 mn
	Comparative #1	Time-step of 10 mn
	Comparative #2	Time-step of 1 hour

Table 19: Face to face scenarios for simulation time step comparison

The results are depicted on Figure 22. Consistently, the 10 minutes simulation time step provides a better approximation of the baseline than the 1 hour time step; but on both cases, some large deviations - respectively of about 10% and 20% - can be observed for the smallest size of battery.

On Figure 23, the simulation graphic representation at the different time steps of a 5 days operation period for the smallest BESS size helps to explain these deviations. They are due to a loss of information, all the more important as the time step is large, concerning the events that have a short duration, such as here the many brief restarts of the fuel generator. Below the figure, an extract of the indicators related to the fuel generator shows that whereas 44 restarts are counted in the minute time step simulation, only 10 of them are observable with the hourly time step for the same 5 days period. This important loss of information is strongly impacting the evaluation of the diesel generator operation costs, and thus the LCOE values computed for the small BESS configurations.

For the large BESS configurations, as the LCOE has a small proportion of OPEX and the generator restarts less frequently due to the larger battery capacity, the impact of the simulation step variation is lower.

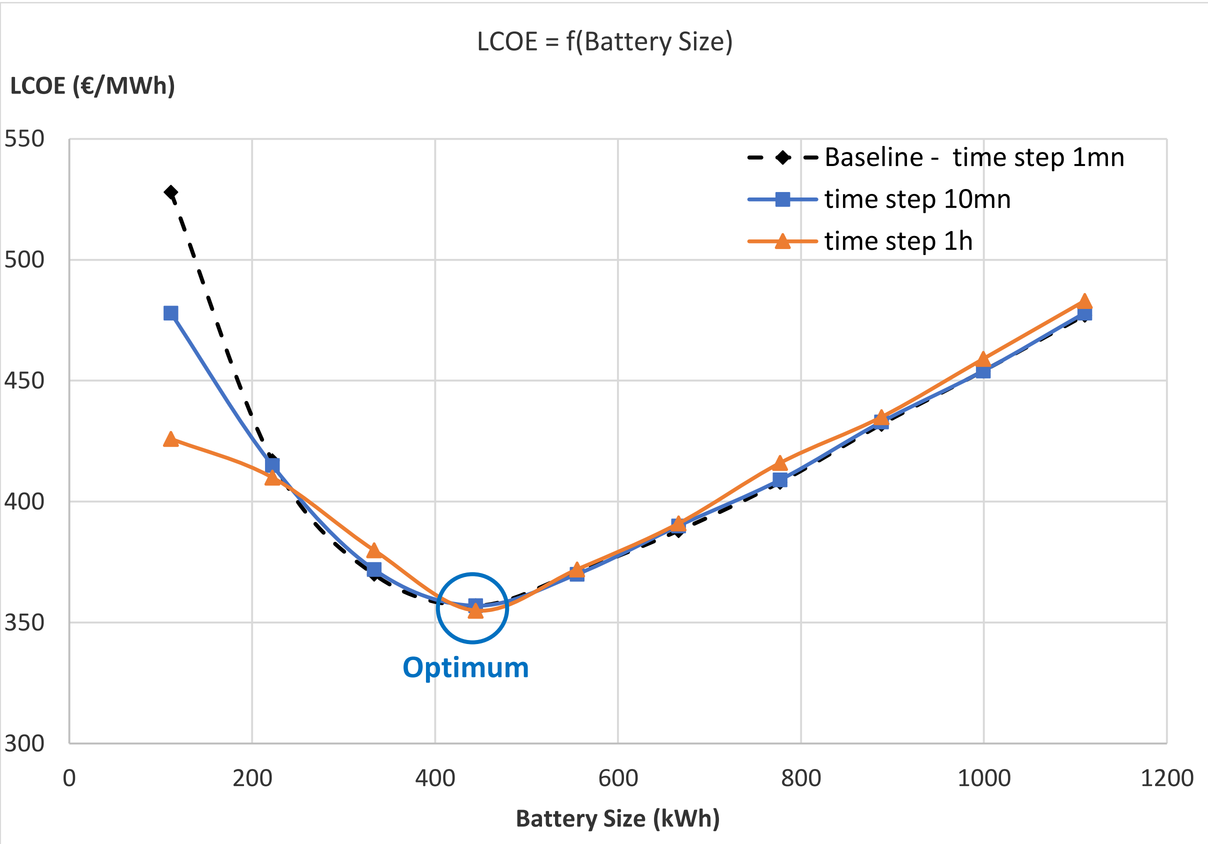
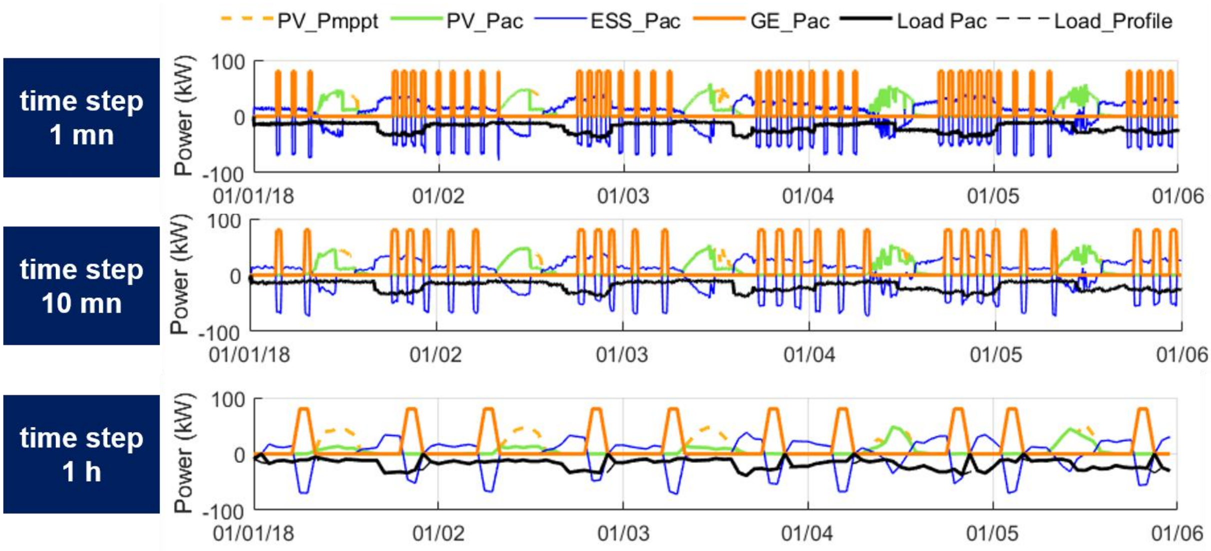


Figure 22: Impact of simulation time step on optimal sizing

	EP_model Time step 1mn	EP_model Time step 10 mn		EP_model Time step 1h	
BESS size (kWh)	**LCOE (€/MWh)**	**LCOE (€/MWh)**	**Relative error**	**LCOE (€/MWh)**	**Relative error**
111	**528**	478	9,47%	426	19,32%
222	**417**	415	0,48%	410	1,68%
333	**370**	372	0,54%	380	2,70%
444	**357**	357	0,00%	355	0,56%
555	**371**	370	0,27%	372	0,27%
666	**388**	390	0,52%	391	0,77%
777	**408**	409	0,25%	416	1,96%
888	**432**	433	0,23%	435	0,69%
999	**454**	454	0,00%	459	1,10%
1110	**477**	478	0,21%	483	1,26%
		Mean error	**1,20%**	**Mean error**	**3,03%**
Computation time / config	hh:mm:ss **00:00:30**	hh:mm:ss **00:00:05**	time reduction factor **6**	hh:mm:ss **00:00:03**	time reduction factor **10**

Table 20: LCOE values obtained through different simulation time steps

It should be noted that the time reduction factor is lower than the time-step ratios when the calculation is reduced to a few seconds, due to some incompressible duration (about 2 seconds) of certain processing operations of the Simulink software.



Indicators	Unit	Time step 1 mn	Time step 10 mn		Time step 1h	
GenSet: time ON	h	**20**	25	+20,62%	30	+46,70%
GenSet: Startups	Number	**44**	27	**-38,64%**	10	**-77,27%**
GenSet: Fuel Consumption	l	**475**	545	+14,83%	629	+32,40%

Figure 23: Impact of different simulation time steps on a 5 days operation period for the smallest BESS configuration (111 kWh)

5.5 Influence of control strategy

In this section is discussed the **influence on optimal sizing of the control algorithms which manage the whole energy system** in regards to the purpose of the application. For a same application case, different control strategy may be implemented, according to the degree of complexity of the control algorithms which have been developed.

For the hybrid microgrid illustrative case, comparison of sizing results is made by separately processing the simulations with 2 different sets of control algorithms:

- The basic control strategy is the one used so far for the baseline. Its main function is to start and stop the diesel generator according to the SOC level of the storage system:
  - When the battery is almost empty (SOC threshold has been set to 10%), the generator is started.
  - When there is a certain quantity of energy in the battery (SOC threshold has been set to 30%), the generator is stopped.

  Its secondary function is to regulate the constant balance between the power generation and the electrical consumption of the load. To fulfil this objective, battery capacity is primarily used as a buffer to compensate for any potential imbalances. In the event of excessive generation and a full battery, the PV production may also be reduced.

- The advanced control strategy is more complex as the generator start and stop operations are no longer managed through SOC thresholds but through an optimization logic which has been implemented thanks to the interface with GAMS software. This **optimization logic aims at minimizing the genset operation costs on a daily horizon**. To achieve this objective, the optimization problem is fed both with a load consumption prediction and a PV forecast, enabling to determine the minimal quantity of additional energy that will be needed from the diesel generator and when it should be produced. As a result, both fuel consumption and genset startup numbers are minimized, leading thus to an operation cost reduction. Concerning the prediction inputs, a real day-ahead forecast has been used for PV and a persistent D+7 prediction has been built for the load consumption as it presents a weekly profile.

As an illustration, Figure 24 compares the resulting operation for a 3-day simulation period between the 2 different control strategies: it can be observed that the fuel generator is started less frequently with the advanced control strategy.

Degree of complexity of control algorithms	*Baseline*	Basic control algorithms
	Comparative	Advanced control algorithms (including optimization)

Table 21: Face to face scenarios for control strategy comparison

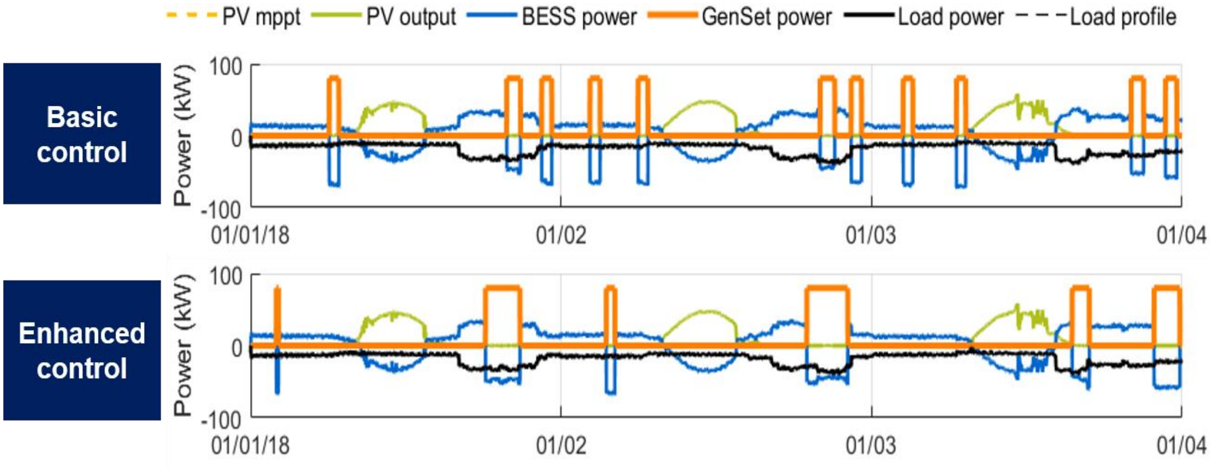


Figure 24: Comparison of simulated operation on a 3-day period with 2 different control strategies (BESS configuration is 220 kWh)

Figure 25 shows that optimal sizing results are strongly affected by the choice of the control strategy, up to the point of changing the optimal BESS size.

For small BESS configurations where the LCOE is mainly composed of OPEX costs, the reduction in operating costs induced by the advanced control strategy is so substantial that it moves the optimum of the LCOE curve from the BESS size of 440 kWh (LCOE value of 357 € / MWh) to a smallest BESS size of 330 kWh (LCOE value of 344 € / MWh). Consequently, thanks to a higher degree of complexity of control algorithms, not only can a smaller BESS be installed, but also a decrease of the LCOE of 3.64% is achieved.

For large BESS configurations where the LCOE is mainly composed on CAPEX costs, the enhanced control strategy doesn't bring any advantage since the operating costs are already very low. LCOE is even a little higher: where the basic control can start the diesel generator to charge largest battery capacities (between SOC 10% and SOC 30%) once only for a period of several days, the optimized control restarts the generator more frequently because of the daily optimisation horizon setup. Some improvements may still be achievable in the advanced control algorithms by fine-tuning the optimisation horizon parameters.

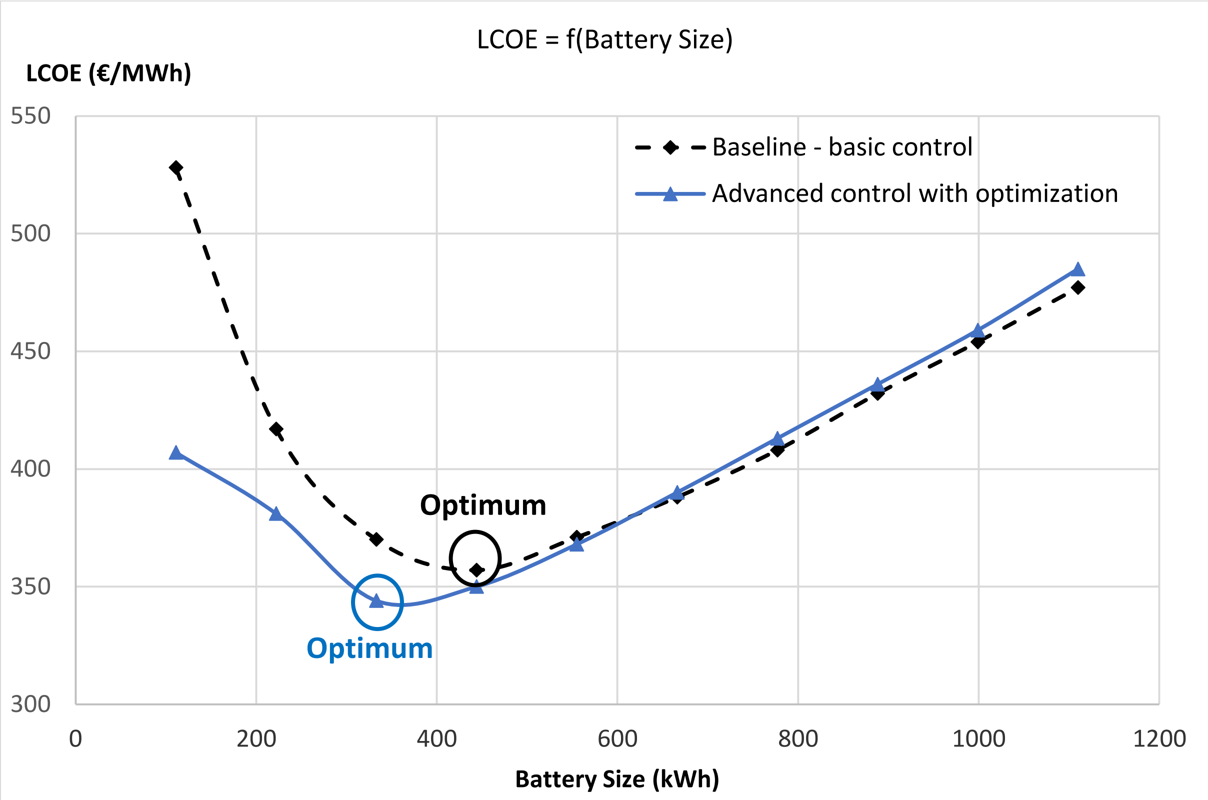


Figure 25: Impact of control strategy on optimal sizing

	Baseline scenario - Basic control strategy	Comparative scenario - Advanced control with optimisation	
BESS size (kWh)	**LCOE (€/MWh)**	**LCOE (€/MWh)**	**LCOE variation**
111	**528**	**407**	-22,92%
222	**417**	**381**	-8,63%
333	**370**	**344**	-7,03%
444	**357**	**350**	-1,96%
555	**371**	**368**	-0,81%
666	**388**	**390**	0,52%
777	**408**	**413**	1,23%
888	**432**	**436**	0,93%
999	**454**	**459**	1,10%
1110	**477**	**485**	1,68%
Optimal LCOE variation between the 2 scenarios			**-3,64%**

Table 22: LCOE values obtained through different control strategies

5.6 Influence of forecast quality

This last section deals with the influence of forecast quality on optimal sizing. As seen in the previous section with the advanced control strategy, some predictive control algorithms may require some power generation or load consumption prognosis. This is also the case for the first illustrative application (BESS application #1) on PV smoothing and peak shaving where a PV forecast is required to announce in advance the power injection profile to the grid operator.

One of the essential characteristics of a forecast is its quality, i.e. the level of errors between this forecast and the actual generation or consumption profile. To anticipate a given phenomenon, it is possible to get different forecasts which differ in their quality, depending on the forecasting technology used, the intelligence of the algorithms used, the data refreshment rate, etc.

This raises the question of **the impact on the optimal size determination of using forecasts which may differ in their quality**. To evaluate this impact with the hybrid microgrid application, optimal sizing results are compared when using the 3 followings forecast time series:

- As the baseline, a **real** PV day-1 **forecast** and load persistence day+7 profile (i.e. the same prediction inputs used in the previous section with the advanced control algorithms).
- As comparative scenario #1, actual PV production and electrical load profile are used as “**perfect forecasts**”, i.e. as virtual error-free forecasts.
- As comparative scenario #2, PV and load consumption enhanced forecasts are computed as the **average profiles** between the realistic forecast used in the baseline and the error-free forecast used in the comparative scenario #1, leading thus to 50% fewer errors than the baseline forecasts.

Forecast quality when predictive control is facing forecast errors	*Baseline*	PV: standard day-1 forecast Load: persistence day+7
	Comparative #1	PV: perfect forecast (actual PV production) Load: perfect forecast (actual consumption)
	Comparative #2	PV: enhanced forecast with 50% fewer errors Load: enhanced forecast with 50% fewer errors (average between baseline and perfect forecasts)

Table 23: Face to face scenarios for forecast quality comparison

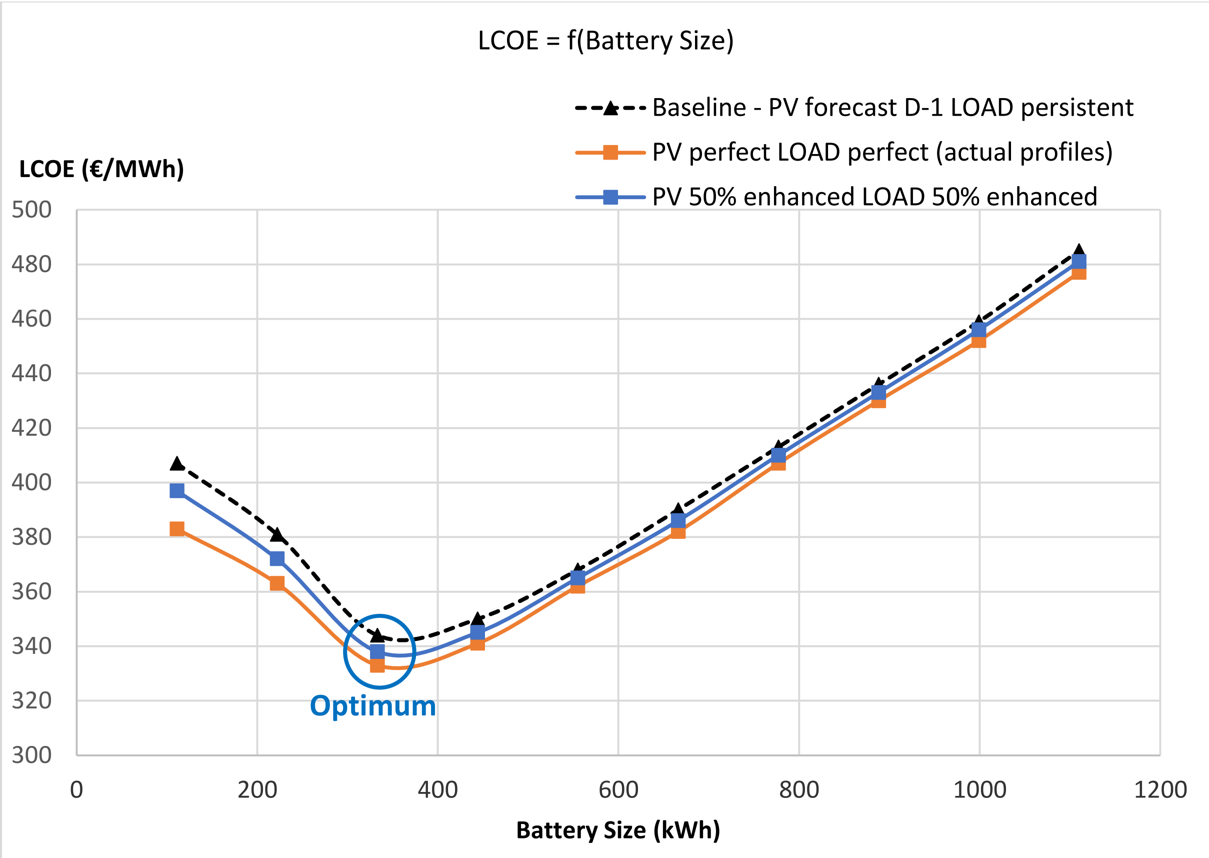


Figure 26: Impact of forecast quality on optimal sizing

	Baseline PV forecast D-1 Load persistent	PV perfect Load perfect		PV 50% enhanced Load 50% enhanced	
BESS size (kWh)	LCOE (€/MWh)	LCOE (€/MWh)	LCOE deviation	LCOE (€/MWh)	LCOE deviation
111	**407**	383	-5,90%	397	-2,46%
222	**381**	363	-4,72%	372	-2,36%
333	**344**	333	**-3,20%**	338	**-1,74%**
444	**350**	341	-2,57%	345	-1,43%
555	**368**	362	-1,63%	365	-0,82%
666	**390**	382	-2,05%	386	-1,03%
777	**413**	407	-1,45%	410	-0,73%
888	**436**	430	-1,38%	433	-0,69%
999	**459**	452	-1,53%	456	-0,65%
1110	**485**	477	-1,65%	481	-0,82%
		Mean deviation	**-2,61%**	**Mean deviation**	**-1,27%**

Table 24: LCOE values obtained through different forecast qualities

The results depicted in Figure 26 show that even if better forecast quality leads to decrease the LCOE, the general shape of LCOE curve is well preserved, which prevents the optimal size value from being moved with a different forecast quality. However, the magnitude of the impact of the forecast quality on the sizing indicator value **highly depends on the application purposes**:

- For BESS application #2 related to the hybrid microgrid, a 50% improvement of the forecast quality induces a decrease of the optimal LCOE value by around 2%.

- For BESS application #1, 50% fewer errors in the forecasts leads to a more significant improvement, with a **difference of 15% on the NPV indicator** used as optimal sizing criteria. This is explained by the fact that the compensation of forecasting errors through the use of the storage system is the main objective in this application: since revenues and penalties are depending on whether or not the injection plan announced in advance is respected, the level of forecast errors has obviously a higher impact on financial indicators.

6 Conclusion

Among the wide range of techniques which can be used to achieve optimal sizing of BESS, the present document described a **deterministic simulation-based methodology** which can be applied for any type of energy system application.

Since the main objective of the study was to **provide a better understanding of the most influencing factors** to consider when determining the optimal size of a BESS, this method was particularly well suited as it offers the adequate level of flexibility to perform various sensitivity analyses.

By using **two** very different illustrative BESS **use cases**, the study enabled to:

- illustrate how this **generic methodology can be applied to different use cases**, for systems composed of various energy components and/or different energy application purposes leading to define different sizing criteria,

- discriminate, among the influencing factors investigated through sensitivity analysis, those whose impact has the same magnitude regardless to the application from those whose impact is application-dependent.

The conclusions of the sensitivity analysis for each of the investigated factors are summarized in Table 25 below:

Factor	Conclusions
Precision of the BESS efficiency behaviour	A variable efficiency behaviour can be approximated by an average efficiency single value without any impact on optimal sizing. However, the average efficiency value must be set precisely since the sizing indicator value is strongly affected by this parameter. An error on BESS efficiency value causes an error bordering on the same magnitude on the sizing indicator.
Degradation of battery capacity due to ageing	Ageing must be taken into account in optimal sizing. In case of limited availability to precise ageing parameters, an estimation of average degradation is sufficient to obtain appropriate confidence levels on sizing indicators.
Degree of technical modelling of the BESS component	Optimal sizing does not require a high degree of technical modelling: a simplified model of BESS directly handling power and energy quantities from global efficiency parameters is adapted and leads to the same sizing indicator values, within a one percent interval, as an in-depth performances model based on equivalent-circuit equations.

Factor	Conclusions
Simulation time-step	The influence of the simulation time-step on optimal sizing strongly depends on the application time constants related to the events impacting the operation costs or incomes. An hourly time-step should in general not be recommended as it could lead to an important loss of information about these events. When such events are related to PV fluctuation or fuel generator operation, like on the 2 illustrative cases, a time-step of 10mn seems suitable.
Degree of complexity of control algorithms	Strong impact: different control strategies may lead to a different optimal BESS size, as illustrated with the hybrid microgrid application. It is therefore recommended to clearly define the control strategy before determining the optimal size.
Forecast quality when predictive control is facing forecast errors	Highly depends on the application purpose: if the main function of BESS is to compensate for forecasting errors in the RE sources, as for illustrative application #1, forecast quality is of the highest importance for optimal sizing: a 50% improvement of the forecast quality induced a difference of 15% of the sizing indicator value for application #1.

Table 25: Sum up of the sensitivity analysis results

At the stage of modelling or collecting data for optimal sizing purpose, these conclusions help to concentrate the effort on the crucial factors which have the strongest influence on the optimal size determination.

In addition, these sensitivity study results enable to identify how calculation time can be significantly reduced within an **acceptable trade-off between the accuracy of the result and the computing time**. As an illustration, by putting together into practice the conclusions related to the use of a simplified BESS model, to the setting of a time-step of 10 minutes and to the ageing estimation by extrapolating a single year simulation, computation time is divided by 840 compared to the baseline scenario, with an average error below 2%. Figure 27 illustrates the resulting optimal sizing curve superimposed to the baseline reference for application #2 and Table 26 compares the LCOE values obtained in both cases as well as the calculation time required for each of the BESS configurations: while each configuration required 1h10mn of computing time with the baseline scenario, it only takes 5 seconds when the conclusions of the study are combined together.

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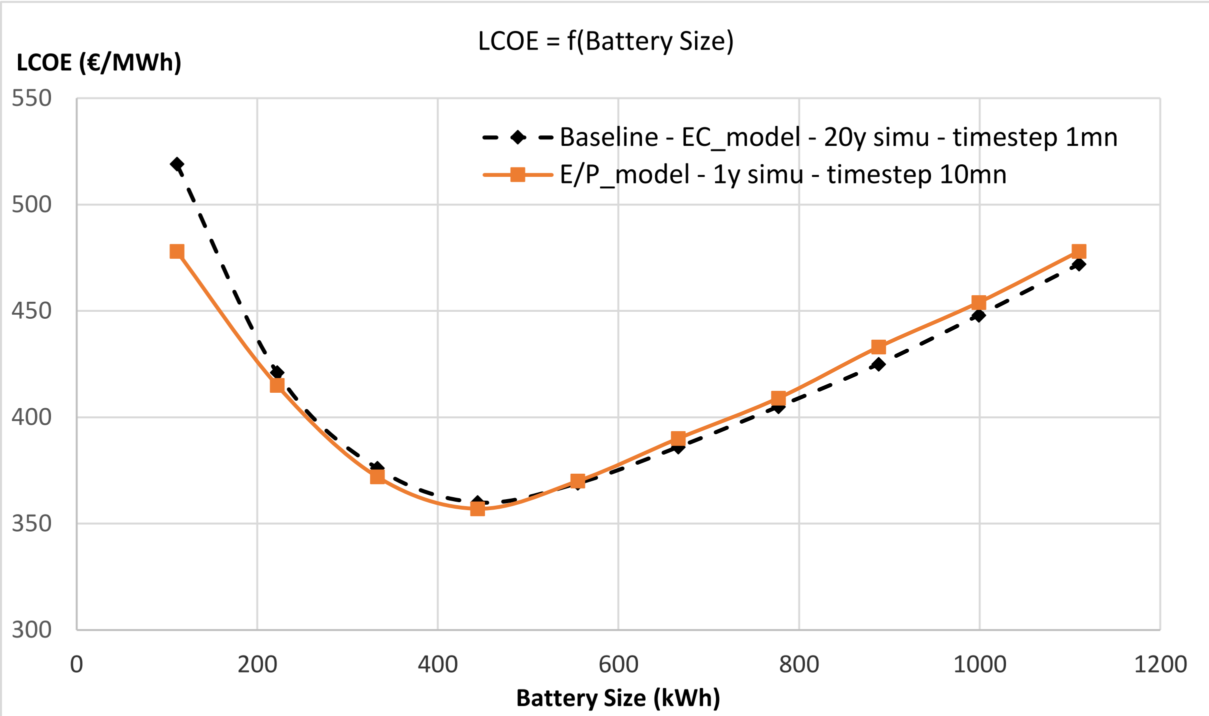

Figure 27: Conclusive approximation with a time reduction factor of 840

	Baseline scenario - EC_model 20y simulation time step 1mn	Approximation - E/P_model 1y simulation time step 10mn	
BESS size (kWh)	**LCOE (€/MWh)**	**LCOE (€/MWh)**	**Relative error**
111	**519**	**478**	7,90%
222	**421**	**415**	1,43%
333	**376**	**372**	1,06%
444	**360**	**357**	0,83%
555	**369**	**370**	0,27%
666	**386**	**390**	1,04%
777	**405**	**409**	0,99%
888	**425**	**433**	1,88%
999	**448**	**454**	1,34%
1110	**472**	**478**	1,27%
		Mean error	**1,80%**
Computation time / config	hh:mm:ss **01:10:00**	hh:mm:ss **00:00:05**	time reduction factor **840**

Table 26: Detailed results for the conclusive approximation

Despite the fact that computing time can be significantly reduced with relevant approximations, this optimal sizing method, well suited for sensitivity analysis, has certain drawbacks related to its deterministic nature:

- it requires to collect a large amount of data,
- it doesn't take into account the uncertainties of specific variables, such as weather related data (irradiance, forecasts) or consumption profiles,
- **a key concern is the need for a large number of simulations** with varying battery capacities to reach the optimum solution.

As it has been mentioned in section 2.2.4 about the hybridisation of different methods, these inherent weaknesses could however be mitigated by further enhancements which could take advantage of the strengths of other techniques such as probabilistic methods or direct search algorithms involving mathematical optimisation or heuristic approach.

At last, it should be pointed out that the optimal BESS sizing performed through this **study was related to single-function applications**, but a further way to make the energy capacity (and by extension the physical size of the BESS) a less critical component is the use of advanced dispatch strategies to achieve multiple functions, allowing an existing BESS to be used more effectively and for system design to more effectively use the energy and power capacity of a BESS.

7 References

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