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MÁSTER UNIVERSITARIO EN INGENIERÍA INDUSTRIAL (MII)

TRABAJO FIN DE MÁSTER

IMPACTO DEL ENVEJECIMIENTO DE LAS BATERÍAS EN MODELOS DE EXPLOTACIÓN DE LA GENERACIÓN

Autor: Teresa Domínguez Larre

Director: Fco. Alberto Campos Fernández

Co-Director: Luis Alberto Herrero Rozas

Madrid

Agosto de 2023

Declaro, bajo mi responsabilidad, que el Proyecto presentado con el título

IMPACTO DEL ENVEJECIMIENTO DE LAS BATERÍAS EN MODELOS DE EXPLOTACIÓN DE LA GENERACIÓN

en la ETS de Ingeniería - ICAI de la Universidad Pontificia Comillas en el

curso académico 2022/23 es de mi autoría, original e inédito y

no ha sido presentado con anterioridad a otros efectos.

El Proyecto no es plagio de otro, ni total ni parcialmente y la información que ha sido

tomada de otros documentos está debidamente referenciada.

Teresa

Fdo.: Teresa Domínguez Larre Fecha: 28/08/2023

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Fdo.: Alberto Campos Fernández Fecha: 28/08/2023

Luis Alberto Herrero Rozas Fecha: 28/08/2023

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Autor: Domínguez Larre, Teresa.
Director: Campos Fernández, Fco. Alberto; Herrero Rozas, Luis Alberto.
Entidad Colaboradora: ICAI – Universidad Pontificia Comillas.

RESUMEN DEL PROYECTO

En este Trabajo Fin de Máster se propone un nuevo modelo matemático para optimizar la operación de las baterías, que permite incluir el coste de degradación y la representación de los ciclos de carga y descarga de las baterías en un problema de despacho económico de manera endógena.

Palabras clave: Sistemas de almacenamiento de energía, envejecimiento, degradación, despacho económico, programación lineal entera mixta.

1. Introducción

Durante las últimas dos décadas, los sistemas de almacenamiento de energía se han convertido en una tecnología fundamental para los sistemas de energía eléctrica [2]. Con el crecimiento de las energías renovables para reducir las emisiones de dióxido de carbono, ha aumentado el interés en el desarrollo del uso de las baterías en estos sistemas. La tecnología de almacenamiento de energía en baterías permite reducir las fluctuaciones de potencia en la demanda eléctrica, aumentar la flexibilidad del sistema y acrecentar la robustez de las tecnologías renovables variables como la energía eólica o la solar [1]. Además, también hay un gran interés en el uso de las baterías de forma que el propietario pueda interactuar con la red almacenando energía en horas de baja demanda y vertiendo esta energía en picos de demanda lo cual permite reducir los costes operacionales [2].

Este interés en el uso de baterías en los sistemas de potencia ha planteado un nuevo reto relacionado con la optimización del uso de éstas con sus peculiaridades características tecnológicas y económicas [3]. Así, se prevé que el coste de fabricación de baterías disminuya, sin embargo, tienen una vida útil limitada debido a los procesos de degradación que tienen lugar durante los ciclos de carga y descarga, resultando en una disminución en la capacidad efectiva de las baterías [2], lo cual implica que la operación de las baterías afecta de forma directa en su vida útil. Además, la mayoría de los costes de operación de estos sistemas de almacenamiento en baterías está asociado a estos costes de degradación, haciendo necesaria su representación en los modelos de despacho económico y de los mercados eléctricos.

2. Definición del Proyecto

Con el aumento del uso de los sistemas de almacenamiento de energía en baterías, se han desarrollado modelos con diferentes niveles de complejidad para optimizar la operación de estas baterías. Estos modelos estudian el funcionamiento de las baterías desde diferentes perspectivas, ya sea teórica o empírica. Los modelos teóricos representan el agotamiento de iones litio u otros materiales activos mientras que los empíricos se basan en el uso de datos experimentales y se diseñan para su aplicación sobre un sistema de baterías especifico [4]. El desarrollo de sendos modelos pone en evidencia la importancia de considerar de forma precisa el envejecimiento de las baterías en los sistemas de almacenamiento. Sin embargo, tanto los modelos teóricos como los empíricos tienen sus propias limitaciones, que quedarán descritas en este documento.

En este Trabajo Fin de Máster se propone un nuevo modelo matemático para optimizar la operación de las baterías, que permite incluir el coste de degradación y la representación de los ciclos de carga y descarga de las baterías en un problema de despacho económico. Este nuevo modelo se entiende como fundamental y de medio plazo porque además de considerar las características técnicas de las baterías proporcionadas por el fabricante, representa su operación en un horizonte temporal de un año. La principal contribución de este proyecto frente a los modelos existentes en la literatura es que permite cuantificar la repercusión en términos de eficiencia computacional y capacidad de representación de los ciclos de carga y descarga modelados de forma endógena.

3. Descripción del modelo/sistema/herramienta

Para el desarrollo del modelo propuesto, se ha tomado como punto de partida el [3], en donde se propone un modelo de despacho económico que introduce el coste de degradación de las baterías como una función lineal, sin comprometer el tiempo de ejecución significativamente. Sin embargo, la optimización de la gestión de las baterías se realiza en dos pasos independientes. Primero, [3] emplea un algoritmo intuitivo para contabilizar el número de ciclos de carga y descarga junto con sus profundidades. En segundo lugar, una vez determinados los ciclos de las baterías se resuelve el problema de despacho económico tomando dichos ciclos como variables de entrada. De esta manera, no se considera la influencia que tiene la operación de las baterías en los ciclos como parte integrante de un sistema en el que además coexisten otras tecnologías incluidas en el despacho económico, obteniendo resultados menos realistas.

Por este motivo, en este Trabajo Fin de Máster se ha desarrollado un modelo matemático que incluye el coste de degradación de la batería de manera endógena como función del número y profundidad de los ciclos determinados por el despacho económico. Se ha elaborado un modelo matemático de optimización de costes con variables enteras, que posibilita la formulación y resolución del despacho económico teniendo en cuenta las fases de carga y descarga de las baterías como resultados inherentes al mismo problema. Esto proporciona una representación más precisa del coste del envejecimiento de las baterías y de su influencia, al mismo tiempo que mejora la coherencia de su integración con las demás tecnologías del sistema.

También se han realizado una serie de casos estudio para comprobar el funcionamiento del modelo a nivel práctico en el mercado ibérico de la electricidad (MIBEL), analizando el efecto de considerar el coste de envejecimiento frente a no considerarlo, la linealización del coste no lineal de degradación y, por último, su eficiencia computacional.

4. Resultados

Para el análisis de resultados se han realizado tres casos estudio basados en el planteamiento de análisis de sensibilidad sobre un caso base que considera como datos de entrada el escenario de los planes de energía y clima para España (PNIEC) y Portugal (PNEC) correspondiente al año 2030.

1. **Caso estudio 1: Análisis de sensibilidad del coste de degradación de la batería**
   Se ha comparado la operación de la batería considerando el coste de degradación de la batería y sin tenerlo en cuenta. Además, se ha hecho un análisis del impacto de la variación del coste de degradación en el modelo, obteniendo los resultados que se muestran en la Figura 1 y la Figura 2.
   En la Figura 1 se representa la operación de la batería sin considerar el coste de degradación, en azul, y considerando el coste de degradación, en naranja. Se puede observar que la penalización debida al coste de envejecimiento afecta a la operación óptima de la batería suavizando las pendientes de carga y descarga como una forma de alargar su vida útil.

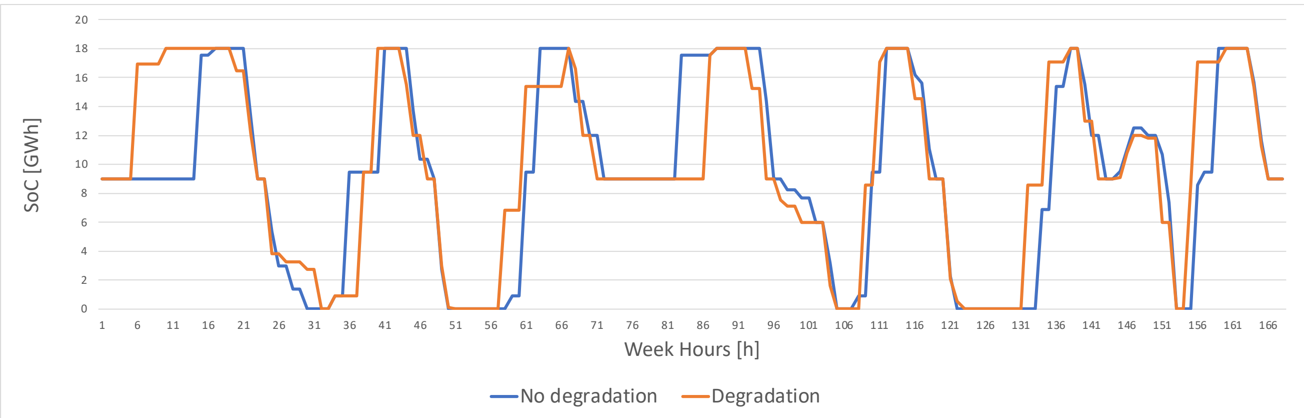

Figura 1. Comparación de la operación de la batería considerando coste de envejecimiento y no considerándolo

En la Figura 2 se representa la operación de la batería para distintos costes de envejecimiento. Se observa que cuanto mayor es el coste de envejecimiento, y por lo tanto, mayor es la penalización en la función objetivo, más se aleja la operación de la batería de su operación ideal, suavizando las pendientes de carga y descarga para alargar su vida útil.

Figura 2. Análisis de sensibilidad del efecto del coste de envejecimiento en la operación de la batería

2. **Caso estudio 2: Análisis de sensibilidad de la aproximación lineal de la función no lineal de degradación**

   En el segundo caso de estudio, se ha comparado el efecto de aplicar un número diferente de tramos en la aproximación lineal de la función no lineal de degradación en el modelo, considerando de uno a cinco tramos.

   En la Figura 3, se representa la operación de la batería al variar el número de tramos en la función de coste de degradación.

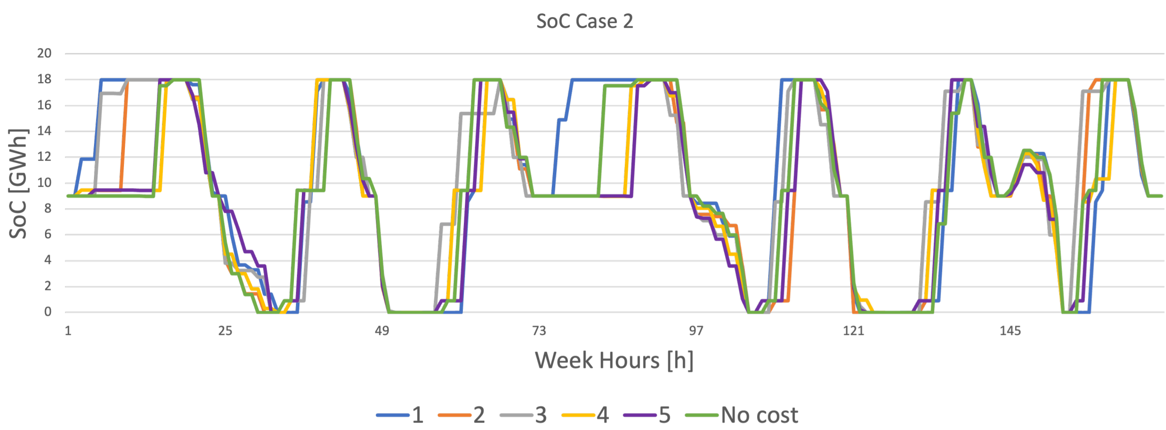

Figura 3. Análisis de sensibilidad del efecto de incrementar el número de segmentos en la linealización de la función estrés

Las Figura 4 y la Figura 5 representan la correlación entre la fluctuación del precio de mercado, representado en línea discontinua negra, y la operación de la batería para un segmento y cinco segmentos respectivamente de la función de coste de degradación, representado en azul. El eje izquierdo representa el nivel de la batería en GWh y el eje derecho representa el precio de mercado en €/MWh. En estas figuras se puede ver con más detalle como el modelo se vuelve más sensible a las fluctuaciones de precio cuanto mayor es el número de segmentos.

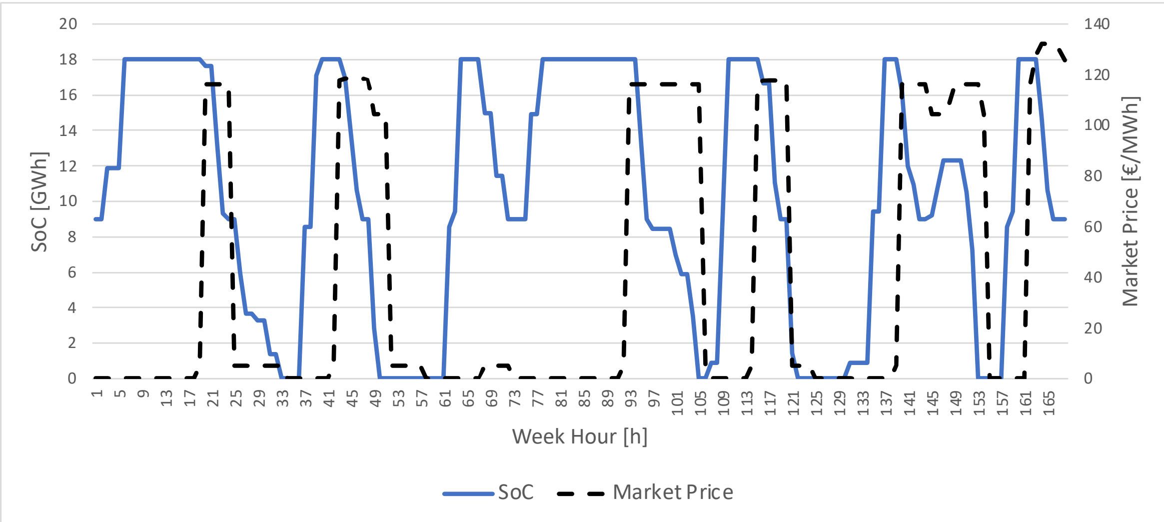

Figura 4. Correlación entre la fluctuación del precio de mercado y la operación de la batería con un único segmento en la función de coste de degradación

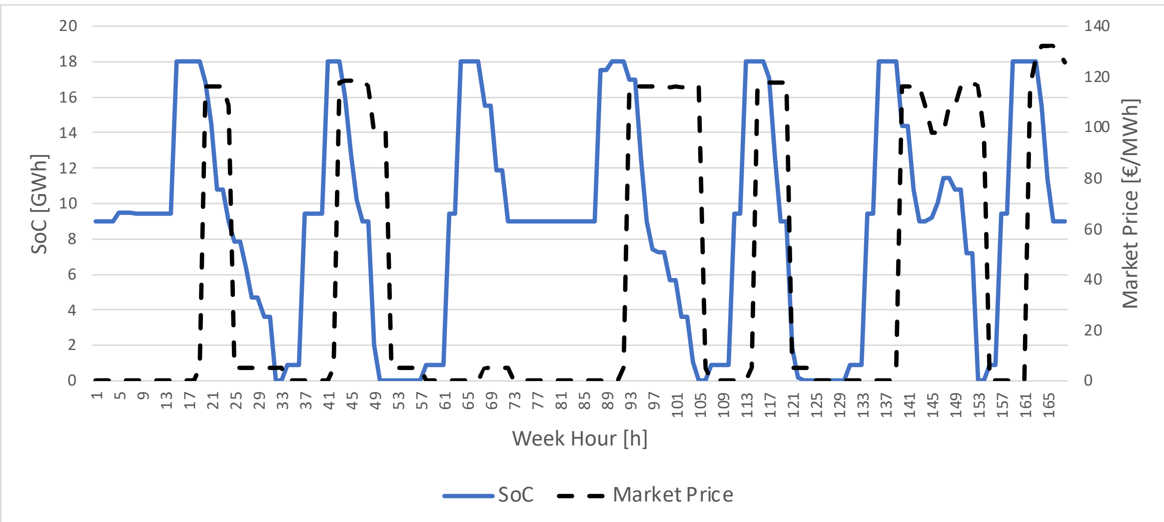

Figura 5. Correlación entre la fluctuación del precio de mercado y la operación de la batería con cinco segmentos en la función de coste de degradación

3. **Caso estudio 3: Resultados computacionales**

Este caso compara los resultados computacionales teniendo en cuenta los tiempos de ejecución cuando se varía el número de ciclos forzados (ciclos mínimos impuestos a través de las condiciones de contorno de la batería, ya sean ciclos diarios, ciclos de "n" días, o ciclos semanales) y el número de tramos utilizados en la aproximación lineal del caso estudio 2.

La Tabla 1 muestra los resultados computacionales de la variación de tiempo de los ciclos forzados. Como se observa en los resultados, cuanto mayor es el tiempo de los ciclos forzados, mayor es el tiempo computacional.

Tabla 1. Resultados computacionales al variar el tiempo de los ciclos forzados

CICLOS FORZADOS	6H	12H	24H	48H	72H
Tiempo de ejecución [s]	87	196	275	612	1054

La Figura 6 y la Figura 7 muestran la correlación entre la fluctuación del precio de mercado, representado en línea discontinua negra, y la duración de los ciclos forzados, representado en azul. El eje derecho representa el nivel de carga de la batería en GWh y el eje izquierdo representa el precio de mercado en €/MWh. Las figuras muestran que si el tiempo del ciclo forzado es muy pequeño, la batería se ve forzada a satisfacer los ciclos forzados, no pudiendo operar según las condiciones del modelo. Por este motivo, cuando se fija el tiempo de los ciclos forzados a 6 horas, la batería no puede seguir la curva de mercado, mientras que, si se amplía el tiempo de los ciclos forzados, se obtiene una mejor relación con la curva de mercado.

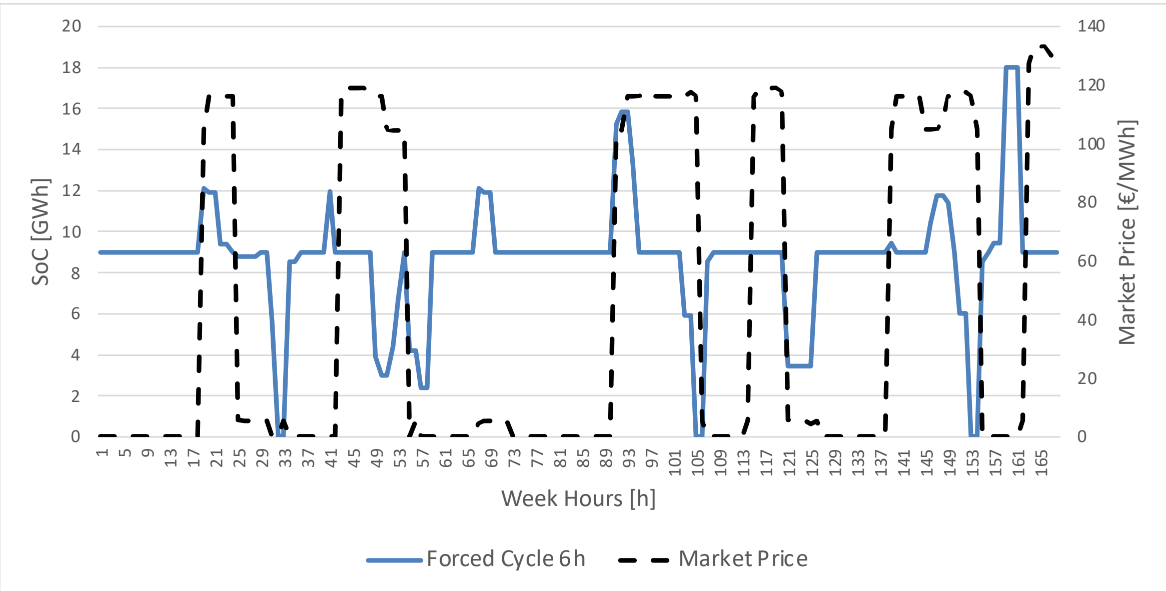

Figura 6. Correlación entre la fluctuación del precio de mercado y ciclos forzados de 6 horas

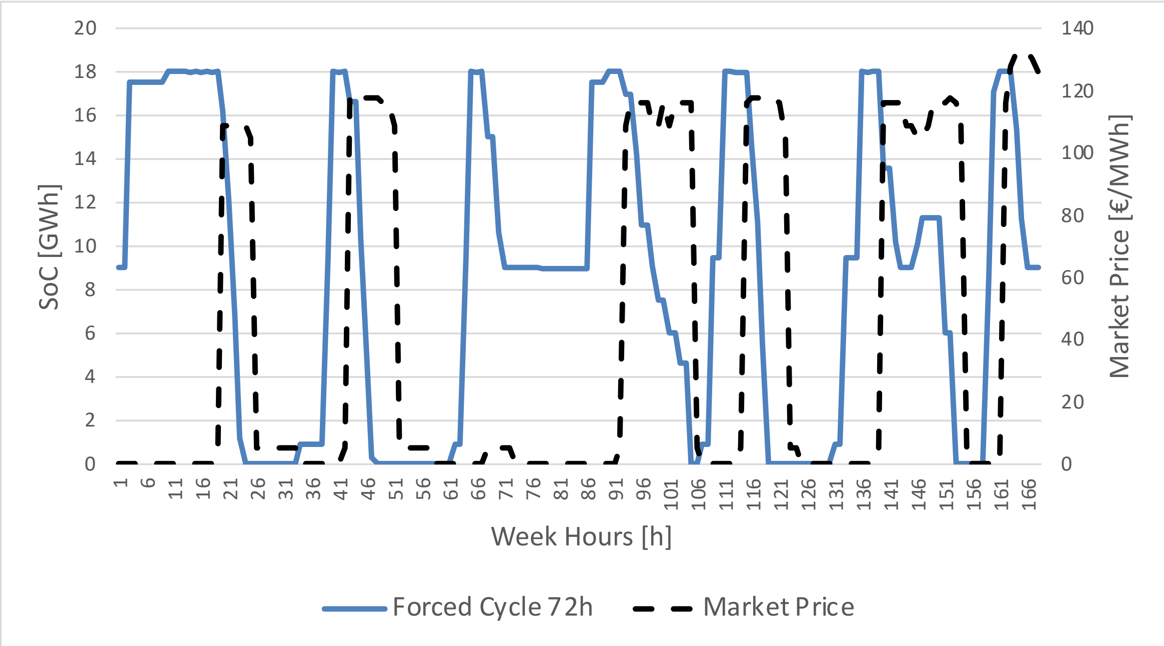

Figura 7. Correlación entre la fluctuación del precio de mercado y ciclos forzados de 72 horas

Los resultados computacionales de la variación del número de segmentos de la función de coste de envejecimiento se muestran en la Tabla 2. Como se muestra en la tabla, los tiempos computacionales tiene una pequeña variación para los casos con 2, 3 y 4 segmentos, mientras que para los casos de 1 y 5 segmentos, los tiempos de ejecución son mayores.

Tabla 2. Resultados computacionales al variar el número de segmentos de la función de coste de envejecimiento

NÚMERO DE SEGMENTOS	1	2	3	4	5
Tiempo de ejecución [s]	332	253	254	287	320

5. Conclusiones

Los sistemas de almacenamiento de energía en baterías tienen potencial para desempeñar un papel importante en el ámbito de la generación de energía. Su habilidad para garantizar la fiabilidad de la red, mejorar su eficiencia e integrar energías renovables resalta la necesidad de mejorar la operación y optimización de estos sistemas para reducir sus costes y extender su vida útil. Si no se considera la degradación de las baterías, se corre el riesgo de que la batería termine su vida útil antes de tiempo lo que puede tener un importante impacto económico. Además de la motivación económica, también hay una motivación medioambiental debido a los materiales con los que se fabrican las baterías que pueden tener un impacto negativo en el medioambiente.

Este Trabajo Fin de Máster presenta un modelo de programación matemática que permite representar un despacho económico incluyendo una función de degradación para optimizar el uso de los sistemas de almacenamiento en baterías. Este modelo considera los ciclos de carga y descarga como variables del problema y es capaz de cuantificarlos de manera endógena.

Los casos de estudio realizados han permitido demostrar la eficiencia computacional y la exactitud del modelo. Los resultados del primer caso muestran que la penalización debido al coste de degradación de la batería aplicada a la función objetivo afecta negativamente la operación óptima de la batería en términos de ingresos de mercado, de forma que pueda extender la vida útil de la batería y optimizar de esta manera su uso. El segundo caso de estudio compara la operación de la batería linealizando la función de coste de envejecimiento con distintos números de segmentos. Los resultados obtenidos demuestran que el modelo se vuelve más sensible a las fluctuaciones en los precios de mercado según aumenta el número de segmentos. El último caso de estudio compara los resultados computacionales relacionados con el tiempo de ejecución cuando se varía el número de ciclos forzados y el número de segmentos. En relación con los ciclos forzados, cuanto mayor es el tiempo de los ciclos, mayor es el tiempo computacional. Sin embargo, si el tiempo del ciclo forzado es muy pequeño, la batería no puede operar con las condiciones del sistema. Por esta razón, es importante encontrar un compromiso entre estas dos condiciones. En relación con el número de segmentos, es importante encontrar el número de segmentos correcto que permite representar la función de coste correctamente sin comprometer el tiempo de ejecución.

Como conclusión, este Trabajo Fin de Máster propone un modelo que permite incluir fácilmente el coste de degradación de las baterías considerando los ciclos de carga y descarga como variables del problema y cuantificándolos de manera endógena. Los casos de estudio realizados han permitido demostrar su eficiencia computacional y precisión.

6. Referencias

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BATTERIES AGEING IMPACT ON GENERATION EXPLOTATION MODELS

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ABSTRACT

A new mathematical model that minimizes the system cost with integer variables that includes the battery degradation cost in an endogenous manner has been designed. This mathematical model formulates and solves an economic dispatch problem considering the charge and discharge cycles of the battery as output variables of the problem, obtaining a better representation of the aging cost and its impact on other model's variables.

Keywords: Energy storage systems (EES), ageing, degradation, economic dispatch, battery energy storage systems (BEES), mixed integer linear programming (MILP).

1. Introduction

Over the past two decades, energy storage systems (EES) have become a crucial component in the electricity generation systems [2]. With the increase in use of renewable energy sources to reduce the use of carbon-emitting technologies, there has been an increase in interest towards the development of these storage technologies. These systems can mitigate power fluctuations, enhance system flexibility, and improve the reliability of variable renewable technologies like wind and solar energy [1]. Additionally, there is a growing interest in the use of energy storage systems in grid-interactive battery projects to enhance grid reliability and reduce operational costs [2].

The rising interest in energy storage systems, has raised concerns regarding the development of operation strategies to optimize the use of batteries [3]. Cost of batteries are expected to decrease. However, batteries have a limited lifespan due to the degradation process that takes place during the charge and discharge cycles, that result in a decrement in their energy storage capacity [2]. This means that the way a battery is operated directly affects its lifespan. Most of the operating costs of these EESs is related to the degradation process associated with their operation, making these degradation costs necessary to be included in the optimization problem of the economic dispatches.

2. Project definition

With the increase in the use of EES, models with different complexities have been developed to optimize the operation of batteries. These models analyze battery performance from two different perspectives, theoretical and empirical models. The first ones focus the representation of the depletion of lithium ions and other active materials while the second ones are based on experimental data and designed for a specific battery energy storage application [4]. The development of these models has emphasized the importance of accurately considering battery degradation in storage systems. However, both types of models have their limitations. During the development of this project, these limitations, together with its influence on the performance of the ESS, will be analyzed. A new mathematical model to optimize the operation of battery energy storage systems (BEES) including its degradation costs, has been developed. This model is considered as a fundamental model for the medium-term analysis, since it only uses the technical characteristics of the batteries provided by the manufacturer for the batteries' operational representation throughout a year of study. The main contribution of this project is to quantify the repercussions in term of computational efficiencies and representation capacities of the charge and discharge cycles when modelled in an endogenous way.

3. Model description

The starting point of this project has been the model presented in [3], which proposes an economic dispatch model that introduces battery degradation cost as a linear function without significantly compromising execution time. However, the optimization problem is performed in two independent steps. First, a straightforward algorithm is used to account for the number of charge and discharge cycles along with their depths. Secondly, these cycles inputted in the economic dispatch problem. Therefore, the model does not consider in an endogenous way the interaction of the battery's operation and their cycles, nor the impact of the degradation costs over the operation of the rest of technologies considered in the economic dispatch, resulting in less accurate results.

During the development of this master's thesis, a new mathematical model that minimize the system cost with integer variables that includes the battery degradation cost in an endogenous manner has been designed. A mathematical optimization cost model with integer variables has been developed, making it possible the state and solve of the economic dispatch considering the battery's charge and discharge cycles as inherent results of the problem itself. This provides a more precise representation of the battery's degradation cost and its influence, improving at the same time a consistent integration with the rest of the technologies of the model.

In addition, a series of case studies have been carried out to verify its performance at a practice level in the Iberian electricity market (MIBEL), analyzing the effect of considering the aging cost versus not considering it, the linearization of the degradation nonlinear cost function, and its computational efficiency.

4. Results

For the analysis of results, three case studies were conducted, each applying a sensitivity analysis over a base case that represent the national energy and climate plans for Spain (PNIEC) and Portugal (PNEC) for 2030.

1. **Case Study 1: Sensitivity analysis of the battery degradation cost**
   In this case study, the battery's operation was compared considering the battery degradation cost and without considering it. In addition, an analysis of the impact on the battery's operation applying different levels of the degradation

costs was performed, resulting in the outcomes shown in the Figure 1 and Figure 2.

Figure 1 represents the battery's operation not considering the degradation cost, represented in blue, and considering it, represented in orange. It can be observed that, due to the penalization imposed by the degradation cost, the optimal battery's is affected softening the charge and discharge cycles as a way to preserve the battery's lifespan.

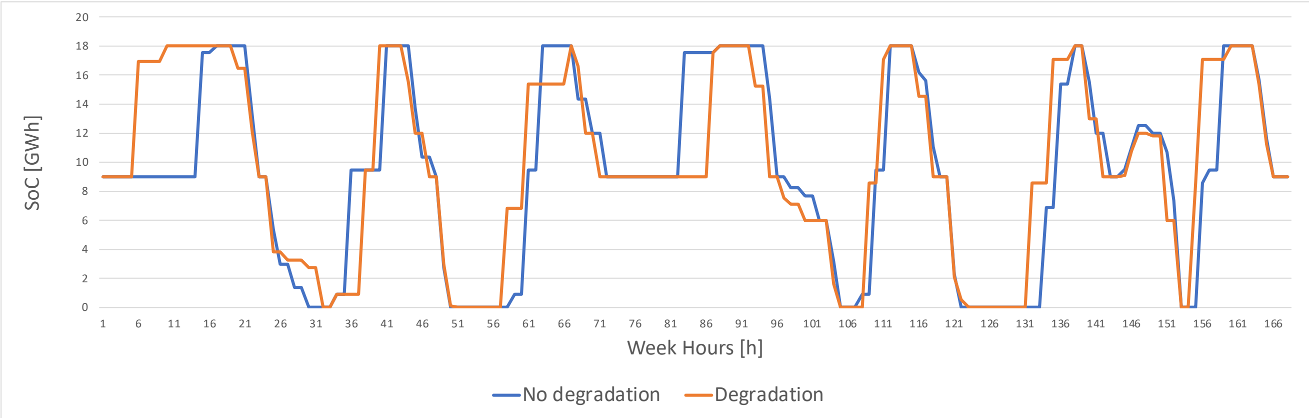

Figure 1. Comparison between considering degradation cost and not considering degradation cost

Figure 2 represents a sensitivity analysis of the effect on the battery's operation for different degradation costs. It can be observed that the larger the degradation cost is, and therefore, the higher the degradation penalization of the objective function is, the further away gets from the battery's optimal operation, making the charge and discharge slopes softer as a way to optimize its lifespan.

Figure 2. Sensitivity analysis of the effect of the degradation cost

2. **Case Study 2: Sensitivity analysis of the degradation cost linear approximation**

The effect of applying a different number of steps in the linear approximations of the nonlinear the degradation function was analyzed in this case study, ranging from one to five steps.

Figure 3 represents the battery's operation when varying the number of segments of the degradation cost function. Figure 4 and Figure 5 show the correlation between the market price fluctuation, in dashed black, and the battery's operation for a single segment and five segments respectively of the degradation cost function, represented in blue. The left axis represents the battery's SoC in GWh, and the right axis represents the market price in €/MWh. These figures show in detail how the model becomes more sensitive to market price fluctuations as the number of segments gets higher.

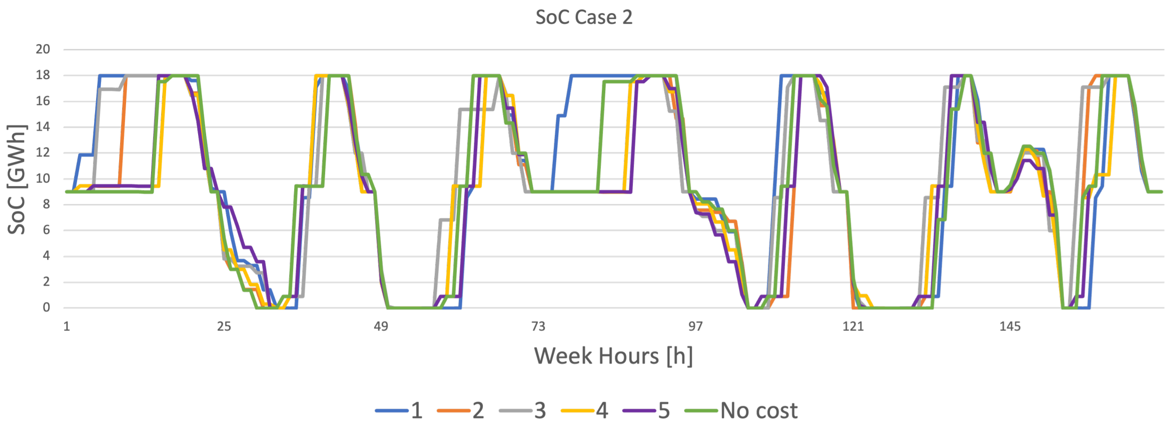

Figure 3. Sensitivity analysis of the effect of increasing the number of segments on the stress function linearization

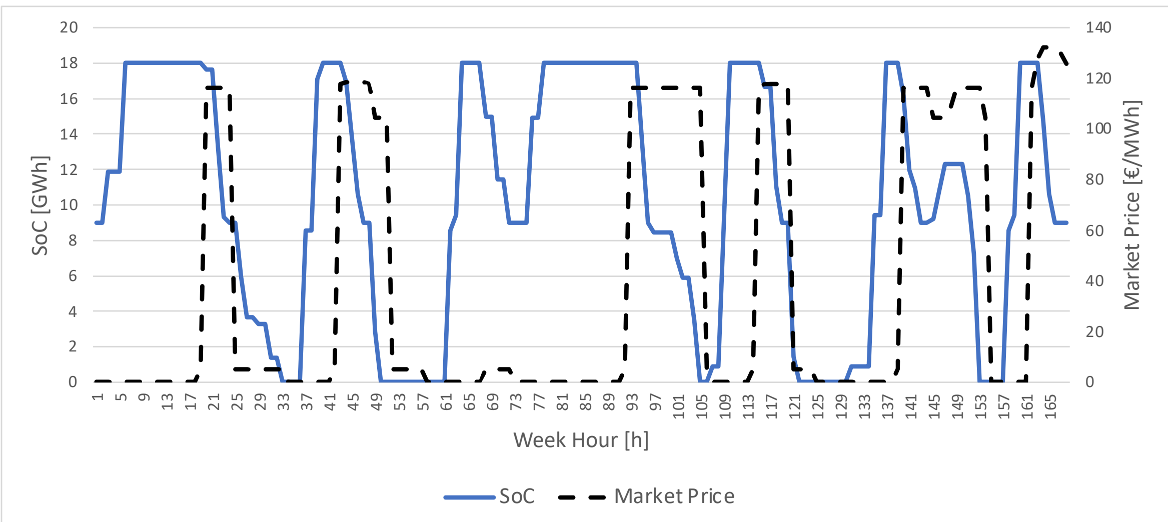

Figure 4. Correlation between the market Price fluctuation and the battery's operation with a single segment in the degradation cost function

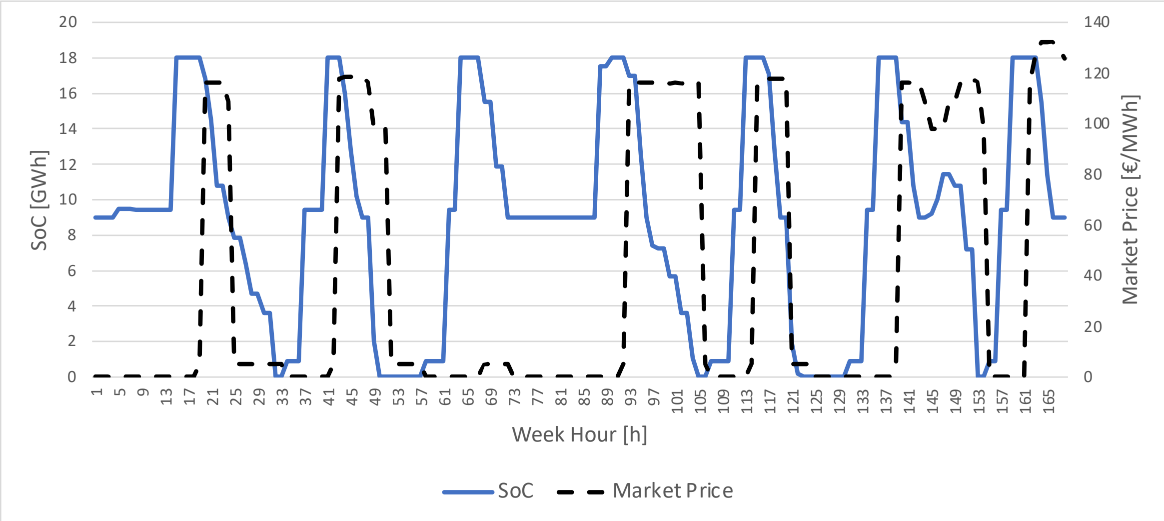

Figure 5. Correlation between the market price fluctuation and the battery's operation with five segments in the degradation cost function

3. Case Study 3: Computational Results

This case study compares the computational results regarding the execution times when varying the number of forced cycles (cycles imposed through the existence of initial and final conditions of the state of charge of the battery at different hours, going from daily cycles or cycles of "n" days length to weekly cycles), and the number of steps used in the linear approximation of the nonlinear aging function of case study 2.

Table 1 shows the computational results obtained when varying the time frame of forced cycles. As it can be seen in the results, as the time of the forced cycles gets higher, the execution time gets higher.

Table 1. Computational results varying forced cycles

FORCED CYCLE	6H	12H	24H	48H	72H
Execution time [s]	87	196	275	612	1054

Figure 6 and Figure 7 represent the correlation between the market price fluctuation, represented in black dashed, and forced cycles' duration, represented in blue. The right axes represents the battery's SoC in GWh and the left axis represents the market price in €/MWh. Figures shows that if the time frame is very small, the battery is forced to do the forced cycles, not being able to operate according to the conditions of the system. As the time frame gets higher, the battery can fulfil the model's conditions. When the forced cycles are set to 6 hours, the battery is not able to follow the market price curve, while as the time frame gets higher, a better fit of the curve is obtained.

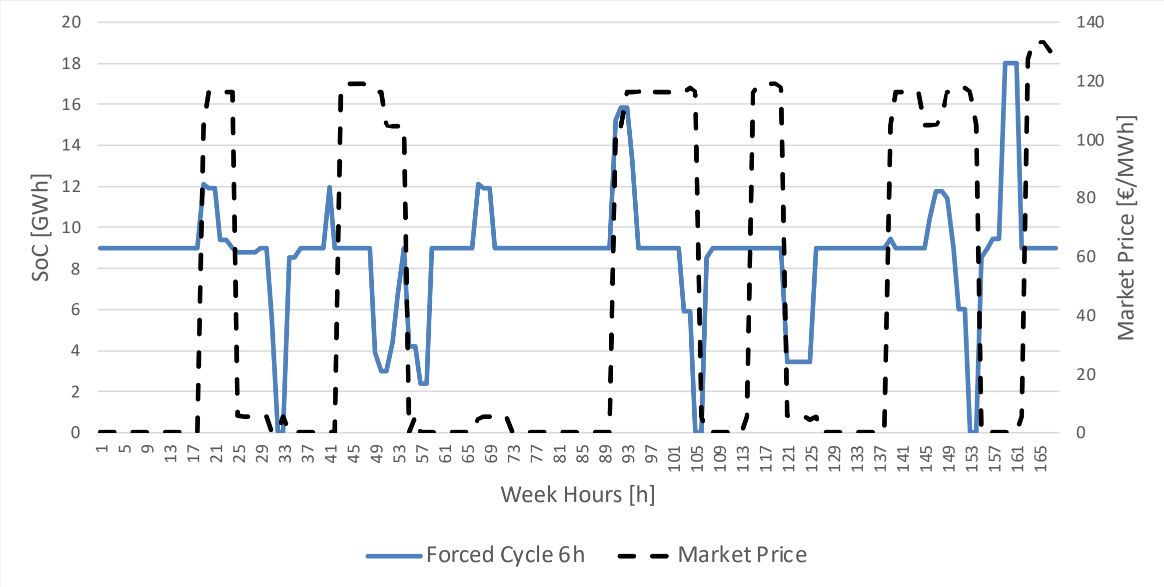

Figure 6. Correlation between market price fluctuation and 6-hour forced cycles

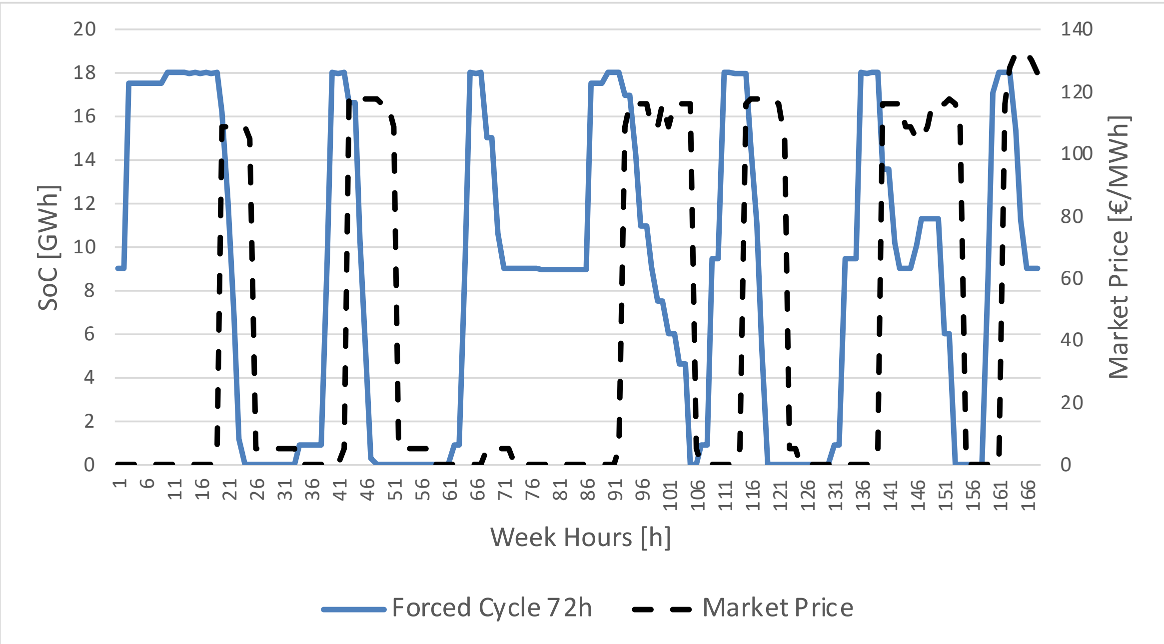

Figure 7. Correlation between market price fluctuation and 72-hour forced cycles

Computational results when varying the number of segments of the degradation cost function are shown in Table 2. As shown on the table, the computational times have a low variation for 2, 3 and 4 segments while for 1 and 5 segments the computational time is longer.

Table 2. Computational times varying the number of segments of the cost function

NUMBER OF SEGMENTS	1	2	3	4	5
Execution time [s]	332	253	254	287	320

5. Conclusions

Energy storage systems have a huge potential to assume an important role on electricity generation. Their ability to ensure reliability, improve efficiency and integrate renewable energy sources highlights the need to improve the operation and optimization of this systems to reduce its cost and extend their lifespan. If battery's degradation is not considered, this can lead to the battery reaching the end of its lifespan too early with its subsequent economic impact. In addition to economic reasons, environmental sustainability reasons are also key factors to optimize the battery's lifespan due to the rare materials they rely on and their impact on the environment.

This thesis has presented a mixed integer linear mathematical programming model that represents an economic dispatch that includes a degradation cost function to optimize the use of energy storage systems considering charge and discharge cycles as variables of the problem quantified in an endogenously way.

The study cases carried out demonstrate the computational efficiency and accuracy of the model. The results of the first case show that the degradation cost penalization applied to the objective function, negatively affects the optimal operation of the battery in terms of market revenue for the energy storage system to extent the battery's life and optimize its use. The second case compares de battery management for piecewise linear cycle aging cost functions with different number of cycle depth segment. The results obtained demonstrate that the model becomes more sensitive to market price fluctuations as the number of segments applied increases. Lastly, the third case compares the computational results regarding the execution times when varying the number of forced cycles and the number segments. In terms of forced cycles, as the time of the forced cycles gets higher, it takes a larger computational time. However, if the time frame is very small, the battery is forced to do the forced cycles, not being able to operate according to the conditions of the system. For this reason, it is important to find a compromise between these two conditions. In terms of the number of segments in the degradation cost function, it is key to find the amount of segments needed to correctly represent the degradation cost function without compromising its computational results.

All in all, this thesis proposes a model that easily enables to include the battery's degradation cost, introducing the charge and discharge cycles as variables of the problem and quantifying them in an endogenously way. In addition, the cases studies demonstrate the computational efficiency and accuracy of the model.

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Nomenclature

Indexes

j	Segments, $j \in N$
t,k	Hours
g	Technologies

Scalars

T	Number of time intervals
J	Number of segments in the cycle aging cost function
G	Number of technologies
ε	Discharge lower bound [MW]

Parameters

η^{ch}, η^{dis}	Charge and discharge efficiencies [%]
E^{max}, E^{min}	Maximum and minimum energy stored in the BES [MWh]
C_j	Marginal aging cost of cycle depth of segment j [€/MWh]
F_g	Variable cost of technology g [€]
D_t	Hourly demand [MW]
G^{max}	Maximum battery discharge [MW]
E^{ini}	Initial energy stored [MWh]
E^{fin}	Final energy stored [MWh]

Positive variables

g_t	Discharge power at time t [MW]
d_t	Charge power at time t [MW]
e_t	Energy stored in marginal cost at time t [MWh]
δ	Total cycle's depth [%]
δ_t	Cycle's depth at time t [%]
$\delta_{j,t}$	Cycle's depth at time t and segment j [%]
$p_{t,g}$	Power produced at time t by technology g [MW]
n_t	Number of cycles until time t

Binary variables

$\alpha_{i,j}$	Activation of cycle *i* in segment *j*
ε_t	Activation of end of cycle at time *t*
$\rho_{1t}, \rho_{2t}, \mu_{1tk}, \mu_{2tk}, \mu_{3tk}$	Auxiliary binary variables for logical implications

Functions

$\phi()$	Stress function [p.u.]

Chapter 1. INTRODUCTION

This chapter presents the role of energy storage systems (EES) and describes the importance of designing an electricity generation model that accurately describes battery ageing to justify the motivation and objectives of this thesis. Finally, the structure of the document will be presented.

1.1 THE ROLE OF ENERGY STORAGE SYSTEMS

Energy storage systems play an important role on the electricity generation systems. It has been a growing interest in the use of these technologies because of the batteries technological advancements developed during the past two decades, the increased in the use of intermittent renewable sources, the limitations in the transmission and distribution infrastructure and the improvement of market regulations [1]. Some applications of energy storage systems include energy arbitrage, transmission and distribution upgrade deferral, transmission congestion relief, load following, voltage support, frequency regulation and the enhancement of renewable energies [2].

- **Energy arbitrage**: It refers to the practice of purchasing low-cost electricity during off-peak hours to charge an energy storage system, and then selling the stored energy when prices are higher during peak periods. This allows participants to take advantage of electricity prices fluctuations, caused mainly by the high integration of renewable energies, and obtain extra profits [3].
- **Transmission and distribution upgrade deferral:** Energy storage systems also provide possible alternatives to traditional distribution planning projects providing capacity upgrades and supporting load growth and reliability needs [4].
- **Transmission congestion relief:** The mismatch between the growth in peak electricity demand and the capacity transmission network additions that has taken place in the recent years, has resulted in the congestion of transmission networks

leading to the need of additional transmission capacity and the increased in charges related to the access of the system. Energy storage systems can be used to mitigate this costs by storing energy during transmission congestion periods and discharging during peak demand hours [2].

- **Load following:** Load following is essential to ensure the reliability and integrity of the transmission system by balancing the electric generation with the demand. Due to its characteristics, energy storage systems are convenient for this purpose because they can operate at partial output levels without significant efficiency or lifespan effects [2].
- **Voltage support:** To maintain the stability of the grid, voltage support controls the injection and absorption or reactive power to ensure that the system remains within the optimal range. While traditionally, this service has been provided by generation resources, energy storage systems offer a viable alternative to address this challenge [2].
- **Frequency regulation:** Frequency regulation matches the generation load with the instantaneous load to maintain the target frequency. Due to its rapid response time, unlike other generators, energy storage systems provide a key advantage providing the required power within seconds instead of minutes [2].
- **Enhancement of renewable energies:** In the rise of renewable energy sources towards decarbonization, energy storage has become a crucial element in the pursuit of this sustainable development. Energy storage systems play a crucial role in mitigating power fluctuations, enhancing the system flexibility and enabling the efficient storage and dispatch of electricity caused by variable renewable energy sources [5].

As explained in the applications presented above, energy storage systems represent a key element to address various challenges to ensure reliability, efficiency, and the integration of renewable energy sources in power systems. Because of this reason, it is importance to optimize their use to reduce operation costs and increase the batteries lifespan.

1.2 ENERGY STORAGE SYSTEMS OPTIMIZATION

Batteries do not require fuel and have minimal operational and maintenance costs. However, they have a limited amount of charge and discharge cycles due to degradation, which reduces the battery's energy capacity and lifespan. Disregarding this degradation process can lead to the battery reaching the end of its life within two or three years. Incorporating a degradation model into operational optimization can balance the revenue gained from the battery's application with the reduction rate of its lifetime, resulting in helping the operators of the batteries to significantly extending the battery's lifespan [1].

In addition to economic reasons, it is also important to limit battery degradation rates for environmental sustainability reasons. Batteries rely on rare materials like nickel and cobalt. Considering their health and environmental impact, the costs of mining and recycling have not been fully accounted. Economically viable batteries should not be treated as disposable items but should be carefully managed to maximize their utilization throughout their lifespan [1].

With the growth in using battery energy storage systems for key power system applications such as energy arbitrage, frequency control, voltage support, peak saving and demand response, it is crucial to develop accurate methods for the assessment of these technologies. Operating costs, predominantly influenced by the degradation of battery cells over time, is an essential aspect of operational planning for battery energy storage systems. Therefore, it is important to develop a model that formulates the degradation process as a function of battery operations [6].

Various models of different complexities have been developed to optimize the utilization of batteries in energy storage systems [1]. These models can be classified into theoretical models, that focus on the depletion of lithium ions and other active materials, and empirical models, based on experimental data and designed for an specific battery energy storage application [6]. However, both types of models have their own limitations, and their representation can influence the optimal operation of the battery energy storage systems. This classification and limitations will be discussed in further detail in Chapter 2.

During the development of this project, a new model for the representation of degradation costs will be proposed. This model will focus on a one-week synthetic period that represents the whole year and is considered a fundamental model that consider a theoretical representation of the ageing cost using the manufacturer technical characteristics of the represented batteries. The main contribution of the model proposed is that quantifies the impact of charge and discharge cycles in an endogenous manner in terms of computational efficiency and representation capabilities, incorporating in this way the degradation of the battery and its lifespan. This model offers significantly accurate results while keeping execution times comparable to other simpler and less accurate approaches found in the literature. Chapter 3. will describe the proposed model and its contributions in further detail.

1.3 MOTIVATION

Modeling battery degradation significantly improves the battery's lifespan and makes the decision-making investment easier [1]. However, it is important to find a balance between the computational complexity of the model and its accuracy. Figure 1-1 shows an overview of some representative battery degradation models present in literature and a comparison of their accuracy and computation complexity. It shows that while sophisticated models may offer greater accuracy, they often require substantial computational resources.

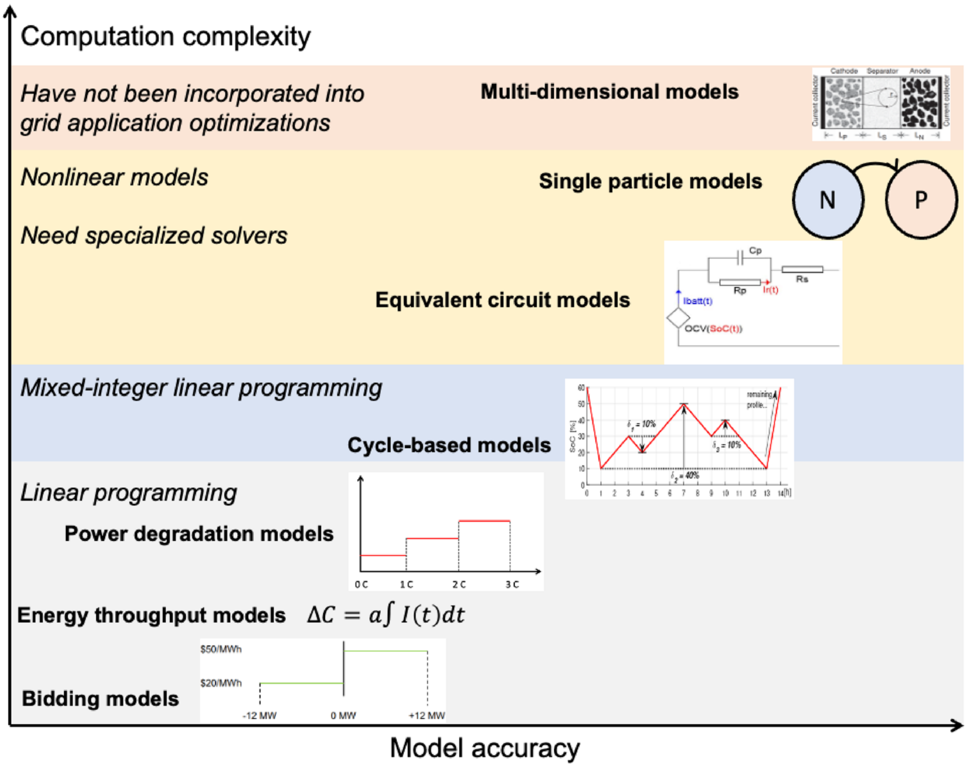

Figure 1-1. Comparison of accuracy and computation complexity of the most representative degradation models present in literature [1]

The model proposed in this project is based on the one proposed in [7]. The authors propose an electricity market model that introduces a linear degradation cost for batteries without significantly impacting execution time. The limitation of [7] is that the optimization process is carried out in two independent separate steps. In the first step, the rainflow algorithm, a straightforward algorithm able of counting cycles and their cumulative, determines the number of charge and discharge cycles. Then, these figures are incorporated as inputs in the economic dispatch of the batteries and other generation technologies, failing to represent how the charge and discharge cycles might affect the cost minimization, resulting in dispatch profiles that might diverge from reality.

As stated before, the model proposed in this thesis will be built upon the findings of [7]. The model is a mixed linear and integer mathematical programming (MILP) model that represents the economic dispatch considering charge and discharge cycles in an endogenous way to achieve a more accurate representation of the power system. The computational efficiency and accuracy will be evaluated in Chapter 4. to determine the practical success of the model.

1.4 OBJECTIVES

This project has two main objectives that will be assessed during its development.

1. Analyze and develop a MILP model that can represent and quantify the charge and discharge cycles and the degradation process of one or a group of batteries of a power system endogenously. For this purpose, the starting point was the optimization model proposed in [7] where the quantification of the charge and discharge cycles and the degradation of the battery are implemented endogenously.
2. Perform and conclude case studies to illustrate the importance of including battery degradation and analyze their computational performance compared to not including it endogenously.

1.5 DOCUMENT STRUCTURE

The thesis is structure as follows. Chapter 2. reviews the degradation models present in literature, compare their different approaches and optimization techniques, and state their contributions and limitations. Chapter 3. describes the model proposed to accurate include the degradation cost of batteries in the economic dispatch optimization model. Chapter 4. presents the analysis of a series of case studies to evaluate the computational complexity and accuracy of the model and Chapter 5. presents the conclusions and future improvements and lines of research.

Chapter 2. STATE OF ART

This chapter presents a review of the degradation models present in literature. The first section presents a brief description of battery ageing mechanisms. The second section presents the main operational stress factors for power-grid applications. The third section describes the classification of the degradation models present in literature. The fourth section classifies the degradation model described in the articles previously analyzed in the third section.

2.1 BATTERY AGEING MECHANISMS

Given the importance of long-term cycling and storage behavior of battery energy storage systems in power systems' applications, there has been a growing interest in developing more sophisticated battery's life-time evaluation techniques. However, understanding the complex processes that take place during battery ageing is not an easy task. This decrease in capacity and power fading is the result of diverse processes and interactions making it necessary to study them at a set, rather than independently, which makes it even more difficult to make an accurate assessment [8]. The battery ageing factors described below are based on lithium-ion batteries because they are considered to have the highest potential for power-grid applications [7].

Over the years, extensive research has been made to investigate the physical and chemical reactions that take place within lithium-ion batteries, resulting in a deeper understanding of the ageing process of various battery structures and defining how battery ageing mechanism can vary depending on external factors [9]. Figure 2-1 shows the external factors that affect the internal ageing mechanisms in a graphic way.

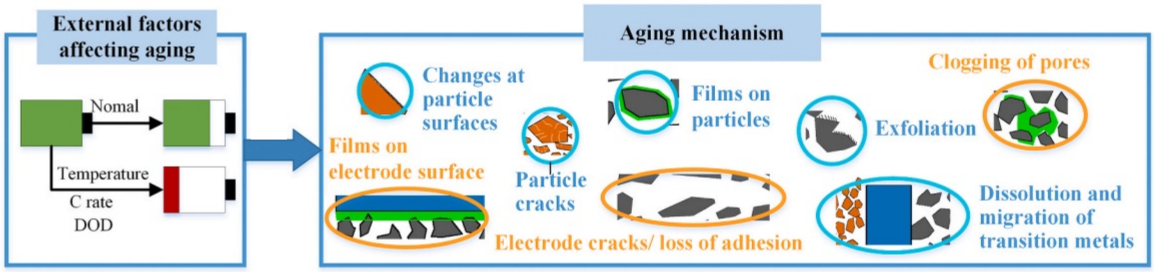

Figure 2-1. Internal aging mechanisms that take place due to the effect of external factors [9]

This internal ageing mechanisms are described using partial differential equations. However, although this models have a good accuracy, they cannot be included in economic dispatch problems [7].

External factors, also known as stress factors when referred to battery degradation models, can be classified according on whether or not they are affected by the way a battery is operated as non-operational factors and operational factors [7]. Only operational factors are considered in battery degradation models for power-grid applications. These stress factors, which are directly affected by the way the battery is operated will be described in further detail on the next section.

2.2 OPERATIONAL STRESS FACTORS

Operational stress factors that have significant impact on battery aging are cycle depth, over charge and discharge, current rate, and average state of charge.

2.2.1 CYCLE DEPTH

This important stress factors allows to create a relationship between the cycle's depth, usually expressed as a percentage, and the amount of charge and discharge cycles that can be performed by a battery. This relationship is defined by the cycle depth-number curved [10]. Figure 2-2 shows an example of a cycle depth-number curve, which is usually provided by the manufacturer.

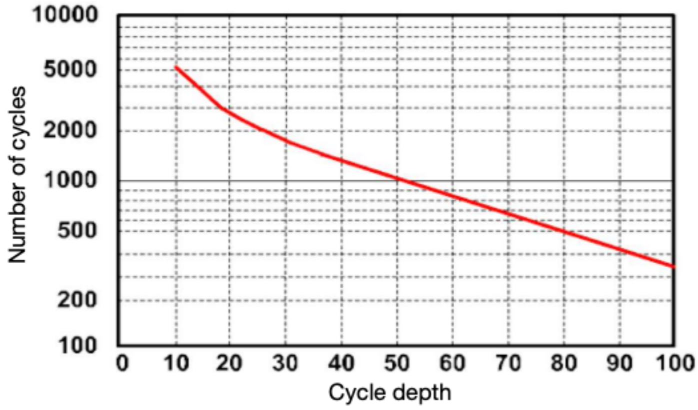

Figure 2-2. Cycle depth-number curve [10]

As shown in Figure 2-2, the battery shown in the example can perform over 5000 cycles of 10% depth while it can only perform 500 cycles of 80% depth. In other words, a battery can perform a larger number of cycles with less deep cycles and a smaller number of cycles with deeper cycles.

2.2.2 CURRENT RATE

Degradation rate is accelerated by high charge and discharge current rates [7].

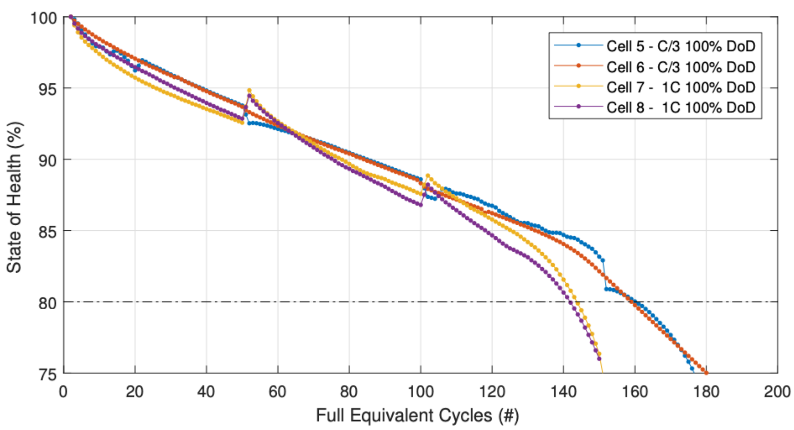

Figure 2-3. Influence of current rate over capacity retention [11]

Figure 2-3 shows the influence of the current rate over the battery's capacity retention. [11] examined four cells by cycle aging, two of them with a current of C/3 and two of them with a current rate of 1C, while other stress factors remained constant. The results show that cells exposed to a higher current rate, significantly reduced their battery life.

2.2.3 OVERCHARGE AND OVERDISCHARGE

Overcharge and overdischarge takes place when the cell is charge or discharge, respectively, outside the voltage threshold determined by the coupling of electrode chemistry forcing electrodes outside their normal range and negatively affecting the battery's life span [12].

2.2.4 AVERAGE STATE OF CHARGE (SOC)

Figure 2-4 shows the results of the calendar ageing test carried out in [13]. It shows the relative values of capacity fade under different calendar aging conditions. Cells with higher SoC, suffered a significantly higher capacity fade than cells with lower SoC.

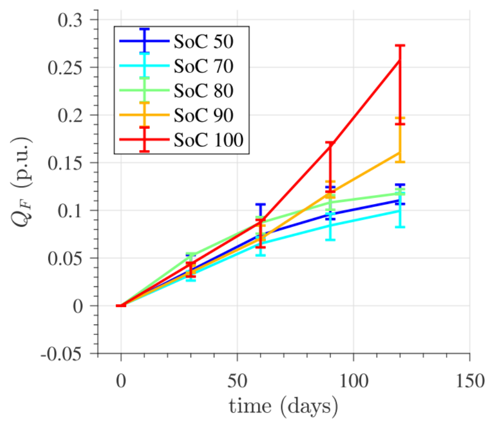

Figure 2-4. Capacity fade under calendar ageing conditions [13]

2.3 DEGRADATION MODELS CLASSIFICATION

Degradation models present in literature can be classified into four main groups according to their approach. Table 1 summarizes this classification and their main advantages and disadvantages.

Table 1. Degradation model classification

MODEL CLASSIFICATION	DEFINITION	MAIN ADVANTAGE	MAIN DISADVANTAGE
THEORETICAL MODELS	Explain batteries' degradation mechanisms and their impact on the battery's state and operation primarily focusing on the depletion of lithium ions and other active materials	Offer accurate results	Difficult to incorporate into the economic dispatch
EMPIRICAL MODELS	Rely on experimental data specific to each battery energy storage application	More suitable for integrating them into the economic dispatch	Constrained by the underlying experimental data, not being applicable to other battery applications and scenarios
SEMI-EMPIRICAL MODELS	Combine theoretical and empirical analysis providing models that offer accurate results operating in conditions and applications different to the ones that apply the experimental data	Offer accurate results for different operating patterns and applications than the ones that apply the experimental data	Risk of over-generalizing
MATHEMATHICAL MODELS	Involve the development and implementation of a mathematical optimization model that incorporates the degradation cost of batteries	They can represent the degradation cost in the objective function as a way to model the replacement cost due to this degradation	They have not been implemented in an endogenous way yet difficulty its incorporation in the economic dispatch

2.3.1 THEORETICAL MODELS

Theoretical models explain batteries' degradation mechanisms and their impact on the battery's state and operation primarily focusing on the depletion of lithium ions and other active materials. They provide explanations of different degradation mechanisms and aim to explain how they affect the battery's usage and conditions. Although they offer accurate results, these models are difficult to incorporate into the economic dispatch because finding a correlation between battery operation patterns and their molecular-level processes is very hard. Table 2 presents the literature of theoretical models.

Table 2. Theoretical models literature

REFERENCE	APPROACH	CONTRIBUTION	MODEL LIMITATIONS	TIME SCOPE	MODEL APPLICATIONS	CONSIDERATIONS	OPTIMIZATION METHOD	BATTERIES	DEGRADATION MODEL	PUBLISH YEAR
[14]	Theoretical	Presents an energy manager for energy storage systems in micro-grids proposing a smart local prediction and a local sheduling algorithm	Does not incorporate global planning	Two months	Micro-grids	Depth of discharge (DoD)	Smart local prediction and local scheduling algorithm	Lead-acid, li-ion and ultra-capacitor	Develops a battery lifetime model that uses the proposed Peukert lifetime energy throughput based on the workload of the battery.	2013

2.3.2 EMPIRICAL MODELS

Empirical models rely on experimental data specific to each battery energy storage application. This kind of model are more suitable for integrating them in economic dispatch analysis. However, they are constrained by the underlying experimental data, not being applicable to other battery applications and scenarios. It is necessary to conduct battery aging experiments specific for the operation conditions and battery application to obtain an accurate empirical model. This process can be time-consuming and have a significant cost impact. Table 3 presents the literature of empirical models.

Table 3. Empirical models literature

REFERENCE	APPROACH	DEGRADATION SIMULATION AND OPTIMIZATION TECHNIQUE	CONTRIBUTION	MODEL LIMITATIONS	MODEL APPLICATIONS	CONSIDERATIONS	OPTIMIZATION METHOD	BATTERIES	DEGRADATION MODEL	PUBLISH YEAR
[15]	Empirical	Proposes the particle swarm optimization-based Feedforward Neural Network (PSO-FNN) for battery aging estimate	Better performance of Particle Swam Optimization (PSO)-Forward Neural Network (FNN) in relatively volatile systems. If there is enough data, the model accuracy is excellent	Enough data availability for reliable results	Battery Management System (BMS)	SoC	The particle swarm optimization-based Feed Forward Neural Network (PSO-FNN)	Li-ion batteries	Battery aging estimate by means of Particle Swam Optimizacion-Foward Neural Network (PSO-FNN)	2020
[16]	Empirical	Electric test to estimate the SoC (DC voltage test and voltage cycling test)	Considers the aging conditions of batteries as inputs of the prognosis model. If there is enough data, the model accuracy is excellent	Enough data availability for reliable results	Li-ion batteries	SoC	It uses the Rao-Blackwellization particle filter, which is able to estimate the posterior values of aging indicators	Li-ion batteries	Uses the Rao-blackwellization algorithm to estimate aging parameters	2019
[17]	Empirical	Neural networks (NN) (Back Propagation (BP) and Fuzzy)	Comparison of two NN SoC estimation strategies, BP and Fuzzy. Superior performance of the FNN. If there is enough data, the model accuracy is excellent.	Enough data availability for reliable results	Li-ion batteries	Current rate (C-rate)	Neural networks (NN) (Back Propagation (BP) and Fuzzy)	Li-ion	Estimation of the battery's SoC by means of Neural Networks	2021

2.3.3 SEMI-EMPIRICAL MODELS

Semi-empirical models combine theoretical and empirical analysis providing models that offer accurate results operating in conditions and applications different to the ones that apply the experimental data. Table 4 presents the literature of semi-empirical models.

Table 4. Semi-empirical models literature

REFERENCE	APPROACH	DEGRADATION SIMULATION AND OPTIMIZATION TECHNIQUE	CONTRIBUTION	MODEL LIMITATIONS	MODEL APPLICATIONS	CONSIDERATIONS	BATTERIES	PUBLISH YEAR
Modeling of Lithium-Ion Battery Degradation for Cell Life Assessment	Semi-empirical	Combination of linear and non-linear components model that uses the rainflow algorithm for cycle counting	Proposes a parameter tunning so that the model can be applied to other types of batteries.	Non-linear model. Two-stage model	BESS	Calendar (temperature (derived from the Arrhenius' equation) and SoC) and cycle (due to charge and discharge cycles; number of cycles, SoC and DoD)	Lithium-ion batteries	2018

2.3.4 FUNDAMENTAL MODELS

Mathematical models involve the development and implementation of a mathematical optimization model that incorporates the degradation cost of batteries. These models consider as an input main technical data provided by the manufacturer, such as the maximum storage energy or the maximum charge capacity. They can represent the degradation cost in the objective function as a way to model the replacement cost due to this degradation. Consequently, if long-term investment decisions are considered, the model can identify the need for installing new batteries when modeling the degradation process of the batteries while computing the charge and discharge cycles. For the short and medium terms, as it is the case of this thesis, they can also represent the cycles when only operation decisions are considered, and accounting for the replacement cost. Unlike the literature, in this project the cycles are represented in an endogenous way in a medium-term dispatch model. Table 5 presents the literature of fundamental models. Table 6 presents the situation of the present project on the actual literature.

Table 5. Fundamental models literature

REFERENCE	APPROACH	DEGRADATION SIMULATION AND OPTIMIZATION TECHNIQUE	CONTRIBUTION	MODEL LIMITATIONS	TIME SCOPE	MODEL APPLICATIONS	CONSIDERATIONS	OPTIMIZATION METHOD	BATTERIES	DEGRADATION MODEL	PUBLISH YEAR
[18]	Fundamental	Relies on the methodology of Model Predictive Control (MPC) for optimal BESS and develops a explicit cost function considering battery degradation (mixed-integer quadratic problem)	Captures nonlinearities and is applicable for arbitrary load patterns. Peak shaving algorithm. It can solve the optimization problem endogenously	Scaled to 1MW	24 hours	BESS	DoD, SoC and current-rate	Methodology of Model Predictive Control (MPC) for optimal BESS operation	Zurich 1MW BESS	Explicit cost function considering battery degradation	2013
[19]	Fundamental	Two-stage stochastic mixed integer linear programming	Proposes a novel optimal generation scheduling model for virtual power plant considering degradation costs of energy storage systems	Applicable for virtual power plants	24 hours	Virtual power plant (WPP (wind power plant), PV power plant (photovoltaic), CTPP (coventional thermal) and battery fleets)	DoD (depth of discharge), ambient temperature	Battery degradation cost modelled and approximated by a piecewise linear function	Lead-acid and nickel metal hydride	Uses the cycle life dependance with the DoD and the ambient temperature by using data points provided by the manufacturer	2016

[20]	Fundamental	Linearization method is proposed to transform the developed degradation model into the MILP optimization problem	Hybrid deterministic/stochastic look-ahead rolling optimization model of wind BESS coordinated operation that includes a linearized battery degradation model	It needs data to perform a test and training period	1 month	Grid-scale BESS's	Shelf degradation (assumed as a straight-line depreciation) and cycle degradation (uses the degradation difference between two regular cycles to estimate degradation of one irregular cycle)	Restricts cycle life degradation and includes the degradation cost in the objective function	Wind-BESS	Battery degradation is set to be the maximum between the shelf degradation, due to normal corrosion process) and cycle degradation	2016
[21]	Fundamental	Defines an utility function as a function of battery power output and battery degradation captured by rainflow cycle-based degradation model	Demonstrates that the rainflow cycle-based degradation cost is convex	Has to be solved in two steps, first the quantification of cycles and then the optimization process	2 hours	Batteries operating in power market	SoC	The objective function maximizes the utility function	BESS	Rainflow cycle-based model for battery degradation calculation	2017

[22]	Fundamental	Stochastic dynamic approach. Proposes three degradation models: fixed per kWh, static multi-factor model and dynamic multifactor model	Comparative analisys of three degradation models	NA	24 hours	Residential customers with solar PV generation and home energy storage system	SoC and DoD	Stochastic dynamic approach	Li-ion batteries	Proposes three degradation models: fixed per kWh, static multi-factor model and dynamic multifactor model	2017
[7]	Fundamental	Rainflow algorithm for assesing battery cycle life and BES optimization market offers iteratively.	Linear cost function degradation model. The model can be easily incorporated into existing market dispatch programs.	Has to be solved in two steps, first the quantification of cycles and then the optimization process	24 hours	Batteries participating in electricity markets	DoD and SoC	Linear optimization and rainflow algorithm	Li-ion	Linear cost function that incorporates the number of charge and discharge cycles previously calculated with the rainflow	2018
[23]	Fundamental	After counting the charge and discharge cycles with the rainflow algorithm, a cycle depth stress function is used to model the life loss.	Adresses the challenge of attacking the complexity of battery degradation function or the lack of future information one at a time	Has to be solved in two steps, first the quantification of cycles and then the optimization process	3 months	BESS	SoC and DoD	The objective function maximizes the net utility of the battery	Li-ion batteries	The battery degradation cost is represented as a function of the charge and discharged cycles, counted by the rainflow algorithm, and quatifying its impact with an stress function	2018

[24]	Fundamental	The model incorporates the degradation effect by reducing the cycleable capacity of the BESS in the problem constraints and defining a degradation penalty in the objective function to avoid excesive cycling	Demonstrates the importance of the location of battery energy storage systems, its proper model representation and the use of advanced algorithms for its resolution	The actual capacity of the battery after cycle degradation is calculated at the end of each day and used for the cycling limit in the next day leading to possible time error	One week	Off-shore wind	DoD, C-rate and SoC	Mixed-integer linear optimization	Lithium nickel manganese cobal oxide	Defining a degradation penalty in the objective function to avoid excesive cycling	2020
[1]	Fundamental	Linear programming and mixed-integer linear programming. Comparison of different battery degradation models	Pros and cons of different battery degradation models and suitability with different battery technologies and configurations	NA	NA	Bulk power systems	C-rate, DoD and SoC	Linear programming and mixed-integer linear programming	Li-ion	Comparison of different battery degradation models	2022

Table 6. Situation of the project on the present literature

REFERENCE	APPROACH	DEGRADATION SIMULATION AND OPTIMIZATION TECHNIQUE	CONTRIBUTION	MODEL LIMITATIONS	TIME SCOPE	MODEL APPLICATIONS	CONSIDERATIONS	OPTIMIZATION METHOD	BATTERIES	DEGRADATION MODEL	PUBLISH YEAR
Batteries aging impact on generation explotation models	Fundamental	Mixed-integer linear programming. Linear degradation cost function	Adresses the problem in an endogeneous way, taking the number of charge and discharge cycles and its depth as variables of the problem	It cannot be used as an expansion model. Adressed in future projects.	1 week	Generation explotation models	DoD and SoC	Mixed-integer linear optimization	Li-ion batteries	Linear degradation cost function optimized in the objective function	2023

2.4 STRESS FUNCTION

To model the life loss of a battery, we use a cycle depth stress function $\Phi(\delta)$. This function depends on the normalized cycle's depth δ, which measures the changes in the battery's SoC. This function implies that a battery can do $\frac{1}{\Phi(\delta)}$ number of cycles before reaching the end of its lifespan. This function is usually provided by battery manufacturers, and it is estimated by means of empirical measurements [10].

[21] makes an analysis of the depth of discharge (DoD) stress functions present in literature. This stress functions include linear stress function, $\Phi(\delta) = k\delta$, exponential stress function, $\Phi(\delta) = k_1 \delta e^{k_2 \delta}$, and polynomial stress functions, $\Phi(\delta) = k_1 \delta^{k_2}$. The linear function can be suitable under some conditions. However, lab tests show that there is a high non-linear relation on degradation under most conditions.

[6] proposes a model applicable for different lithium-ion batteries providing methods for model coefficients tunning for the power degradation stress function by means of manufacturer's data.

[25] provides a power degradation stress function based on the influence that material parameters of the battery and its operational conditions on the diffusion induced stress (DIS), related to the cycle aging, and the solid electrolyte interphase (SEI).

[26] proposes a new aging model based on theoretical models of crack degradation and provides an exponential dependence on depth of discharge stress.

For the purpose of this project, the stress function used in article [7]. Its near-quadratic stress function, defined in E. 1, provides a good representation of the battery's life loss caused by the depth of discharge.

E. 1 $$\phi(\delta) = (5.24E^{-4})\delta^{2.03}$$

Chapter 3. PROPOSED MODEL FOR BATTERY DEGRADATION

This chapter describes the proposed MILP model that includes the optimization of the battery's degradation costs in the economic dispatch. The first section describes the hypothesis considered. The second section presents the objective function, and the third section formulates its constraints. Finally, the last section summarizes the final formulation of the model.

3.1 HYPOTHESIS

The proposed model represents an economic dispatch, which optimizes the exploitation of the power system to obtain the minimum total system cost maintaining the balance between electric demand and generation. In addition to the classic economic dispatch objective function and constraints [27], this model includes a degradation battery cost minimized in the objective function and its respective constraints related to the count of charge and discharge cycles and the battery degradation.

The hypothesis considered in this model are:

- The degradation of the battery is produced by the **number and depth** of the charge and discharged **cycles** performed by the battery.
- **Other degradation factors**, such as the charge and discharge speed or temperature, **will not be considered**.
- It is assumed that the **initial and final conditions** of the battery **match with the time frame (i.e., the state of charge, SoC, of each battery at the beginning of the timeframe coincides with the SoC at the end).** In addition, for the development of the study cases, forced cycles of 24 hours have been used. These forced cycles are

used to force the battery to have an specific SoC at the end of this 24 hour cycles providing a better analysis of the battery's performance.

- It is assumed that the **aging cycles** are **only produced during the battery's discharge**. As in [7]; this assumes that a half discharge cycle produces the same aging as a complete charge and discharge while a half charge cycle does not produce aging. This is a reasonable assumption because the amounts of energy charged and discharged from a battery are almost identical in each forced cycle.
- A cycle's depth δ at time *t* depends on the discharged power at that same instant *t*, as showed on equation E. 2.

$$E.\ 2 \qquad \delta(g_t) = \frac{1}{\eta^{dis} E^{max}} g_t$$

- **No investment decisions** will be considered.
- It is a single-node model; therefore, neither the distribution, nor the transport grid together with their losses are considered.
- The secondary or the tertiary reserves are not represented.

3.2 *MAIN INPUTS AND OUTPUTS*

The main inputs and outputs considered in the model will be presented in this subsection. For simplification, only the inputs and outputs related to the battery's operation optimization will be presented. Other inputs and outputs considered in this model can be consulted in [28].

3.2.1 INPUTS

- **Cycles' depth stress function.** The stress function used in the model is shown on equation E. 3. This equation represents the incremental aging resulting from the battery's cycle depth δ.

$$E.\ 3 \qquad \phi(\delta) = (5.24E^{-4})\delta^{2.03}$$

Figure 3-1 represents the stress function used in the model.

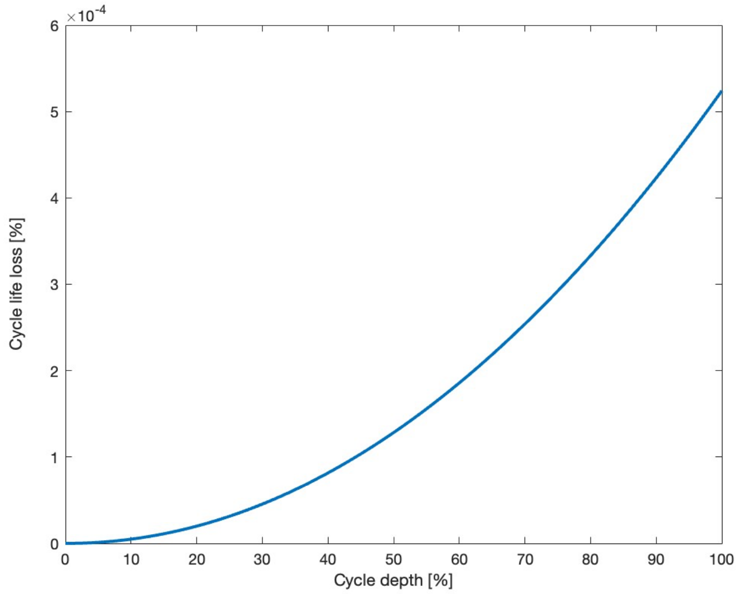

Figure 3-1. Stress function

- **Battery's main technical characteristics.** The input technical characteristics of the battery used in the model and its units are listed on Table 7.

Table 7. Battery's input parameters

Parameter	Units
Charging performance	%
Discharging performance	%
Installed power	GW
Maximum SoC	GWh
Minimum SoC	GWh
Maximum discharge and charge power	GW
Battery's initial level	GWh
Cell replacement cost	€/kWh

- **Forced cycles.** As explained on subsection 3.1, forced cycles are used to have a better representation of the battery's operation.

3.2.2 OUTPUTS:

- **Number of cycles performed.** The methodology used to count the cycles performed by the battery will be explained on subsection 3.5.3.
- **Cycles depth.** The battery's cycle depth is described by equation E. 2.
- **Battery aging.** The battery aging is defined by equation E. 4, which is the total stress of all the identified cycles suffered by the battery.

$$E.\ 4 \qquad \phi = \sum_{n=1}^{N} \phi(\delta_n)$$

3.3 THE AGING COST

The aging cost $C(g_t)$ is defined by the replacement cost of the cells R with the stress $\phi(\delta(g_t))$. Equation E. 5 shows the aging cost definition.

$$E.\ 5 \qquad C(g_t) = R\phi(\delta(g_t))$$

To calculate the marginal cost, equation E. 5 is derived with respect to the discharged power, obtaining equation E. 6.

$$E.\ 6 \qquad \frac{\partial C(g_t)}{\partial g_t} = R\frac{\partial \phi(\delta(g_t))}{\partial g_t}$$

Applying the chain rule, equation E. 7 is obtained.

$$E.\ 7 \qquad \frac{\partial \phi(\delta(g_t))}{\partial g_t} = \frac{d\phi(\delta)}{d\delta}\frac{\partial \delta(g_t)}{\partial g_t} = \frac{d\phi(\delta)}{d\delta}\frac{1}{\eta^{dis}E^{max}}$$

The marginal aging cost is defined by equation E. 8.

$$E.\ 8 \qquad \frac{\partial C(g_t)}{\partial g_t} = R\frac{d\phi(\delta)}{d\delta}\frac{1}{\eta^{dis}E^{max}}$$

ϕ can be linearly approximated by J segments equally speciated in interval [0,1] as shown in equation E. 9.

$$E.\ 9 \qquad \frac{\partial C(g_t)}{\partial g_t} = \frac{R}{\eta^{dis} E^{max}} \cdot \frac{d\phi(\delta)}{d\delta} = \left\{ \begin{matrix} c_1 \ if \delta \in \left[0, \frac{1}{J}\right) \\ \dots \\ c_j \ if \delta \in \left[\frac{j-1}{,J}, \frac{j}{J}\right) \\ \dots \\ c_J \ if \delta \in \left[\frac{J-1}{J}, 1\right) \end{matrix} \right\}$$

Equation E. 10 defines the battery's degradation cost.

$$E.\ 10 \qquad c_j = \frac{R}{\eta^{dis} E^{max}} J \left[\phi\left(\frac{j}{J}\right) - \phi\left(\frac{j-1}{J}\right)\right]$$

3.4 *OBJECTIVE FUNCTION*

The objective function, defined in equation E. 11, consists in the minimization of the production costs of each electricity generation technology and the degradation costs of the batteries of the system. For the sake of simplicity only one battery is considered in the formulation here presented.

$$E.\ 11 \qquad C = \sum_{t=1}^{T} \left(\sum_{g=1}^{G} F_g p_{t,g} + \sum_{j=1}^{J} C_j \delta_{j,t} \frac{1}{\eta^{dis} E^{max}}\right)$$

The objective function consists of two main terms:

- $F_g p_{t,g}$ is the production cost of technology *g* during time *t*.
- $C_j \delta_{j,t}$ is the degradation cost of the battery in segment *j* during time *t.* The model minimizes the degradation cost of each of the batteries of the system.

3.5 *CONSTRAINTS*

For simplicity, only the constraints related to the battery operation are explained in this subsection. The remaining constraints are explained in detail in [28].

The model comprises four groups of constraints: 1) production-demand balance equation, 2) state of charge (SoC) of the battery, 3) count of the number of cycles, 4) definition of the depth of the cycle.

3.5.1 PRODUCTION-DEMAND BALANCE

Equation E. 12 defines de production-demand balance. The energy produced by all the technologies and discharged by the batteries of the system must be equal to the demand and the energy charged by the batteries.

$$E.\ 12 \qquad \sum_{g=1}^{G} p_{t,g} + g_t = D_t + d_t$$

- $p_{t,g}$ is the power produced at time *t* by technology *g*
- g_t is the discharge power of the battery at time *t*.
- D_t is the demand of the system at time *t*.
- d_t is the charge power of the battery at time *t*.

3.5.2 BATTERY'S STATE OF CHARGE (SOC)

The SoC is the amount of energy available in a battery at a specific point in time. Figure 3-2 shows an example of a battery's SoC profile but expressed as a percentage.

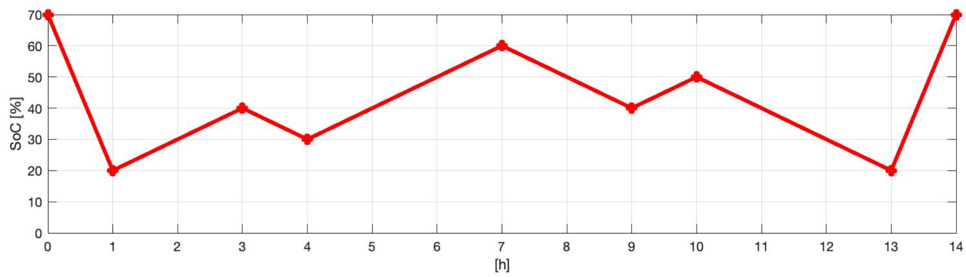

Figure 3-2. Example of SoC profile

The SoC expressed in energy is defined in equation E. 13, which defines the stored energy evolution in each time as the SoC in the previous time plus the charge and minus the discharge, taking into account the corresponding efficiencies. Equation E. 14 limits the maximum and minimum SoC of the battery and equations E. 15 and E. 16 define the initial and final values of the battery, which has been established in this formulation for the last and the first times of the time horizon (however, other shorter forced cycles can be also set).

$$E.\ 13 \qquad e_t = e_{t-1} + d_t\eta^{ch} - \frac{g_t}{\eta^{dis}}$$

$$E.\ 14 \qquad E^{min} \leq e_t \leq E^{max}$$

$$E.\ 15 \qquad e_1 = E^{ini}$$

$$E.\ 16 \qquad e_T = E^{end}$$

- e_t is the energy stored at time t.
- η^{ch}, η^{dis} are the charge and discharge efficiencies respectively.
- E^{max}, E^{min} are the maximum and minimum energy that can be stored in the battery respectively.
- E^{ini}, E^{end} are the initial and final values of the energy stored in the battery respectively.

3.5.3 Number of Cycles Count

The binary variable ε_t is defined to count the number of cycles n_t. Variable ε_t activates at time t if the battery is discharging at the previous time t-1 and it stops discharging at the actual time t. Equation E. 17 is the logical implication used.

$$E.\ 17 \qquad If\ g_{t-1} > 0\ and\ g_t \leq 0 \rightarrow \varepsilon_t = 1$$

Equations E. 18, E. 19, E. 20, E. 21 and E. 22 are the restrictions defined to model the logical implication in E. 17 applying the methodology explained in Annex II. Logical Prepositions Model Methodology. Equation E. 23 defines the number of cycles at time t. Equation E. 24 defines the binary variables.

$$E.\ 18 \qquad g_{t-1} \leq \rho_{1t}(E^{max})$$

$$E.\ 19 \qquad g_t - \varepsilon \geq \rho_{2t}(-\varepsilon)$$

$$E.\ 20 \qquad \rho_{1t} + \rho_{2t} = 1 + \varepsilon_t$$

$$E.\ 21 \qquad g_{t-1} - \varepsilon \geq (1 - \varepsilon_t)(-\varepsilon)$$

$$E.\ 22 \qquad g_t \leq (1 - \varepsilon_t)(E^{max})$$

$$E.\ 23 \quad n_t = \sum_{t'=1}^{t} \varepsilon_{t'}$$

$$E.\ 24 \quad \rho_{1t}, \rho_{2t}, \varepsilon_t \in \{0, 1\}$$

- ε_t is a binary variable that gets active if a discharge cycle ends at time *t*.
- ε is a lower bound for the discharge g_t. The definition of this parameter is explained in more detail in Annex II. Logical Prepositions Model Methodology.
- ρ_{1t}, ρ_{2t} are auxiliary binary variables used for the logical implication defined in E. 17 (see Annex II. Logical Prepositions Model Methodology for more details).
- n_t is the number of cycles at time *t*.

Figure 3-3 shows the points of the SoC battery profile expressed as a percentage where variable ε_t is activated.

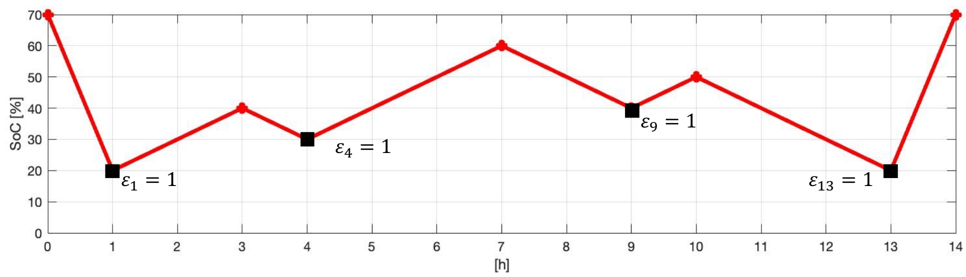

Figure 3-3. Activation of variable ε_t in the SoC profile

3.5.4 CYCLE'S DEPTH

The cycle's depth is measured as a percentage. Equations E. 25 and E. 26 define the total cycle's depth δ along the temporal horizon and the corresponding depth δ_t at each hour, respectively. Equation E. 27 set the bound of the cycle's depth $\delta_{j,t}$ for each segment (or step). Note that only one segment must be activated according to equation E. 28. Equation E. 29 defines $\alpha_{j,t}$ as a binary variable.

$$E.\ 25 \quad \delta = \sum_{t=1}^{T} \delta_t$$

$$E.\ 26 \quad \delta_t = \sum_{j=1}^{J} \delta_{j,t}$$

$$E.\ 27 \quad \left(\frac{j-1}{J}\right)\alpha_{j,t} \leq \delta_{j,t} \leq \frac{j}{J}\alpha_{j,t}$$

$$E.\ 28 \quad \sum_{j=1}^{J} \alpha_{j,t} = 1$$

$$E.\ 29 \quad \alpha_{j,t} \in \{0, 1\}$$

- δ is the total depth of all the cycles performed during the temporal period.
- δ_t is the cycle's depth at time *t*.
- $\delta_{j,t}$ is cycle's depth at segment *j* at time *t*.
- $\alpha_{j,t}$ is the binary variable that activates only one of the segments.

Equation E. 30 sets the definition of the cycle's depth δ_t using a logical implication. This implication sums the discharge values between two consecutive cycles assigning the result to the cycle's depth variable, δ_t. The calculation is only performed at the end of a cycle, i.e., when $\varepsilon_t = 1$. Equations E. 31, E. 32, E. 33 and E. 34 are the constraints used to define it applying the methodology explained in Annex II. Logical Prepositions Model Methodology. Equation E. 35 defines the binary variables.

$$E.\ 30 \quad If\ \varepsilon_t = 1\ and\ \sum_{t'=t-k,t} \varepsilon_{t'} = 1 \rightarrow \delta_t \geq \frac{1}{\eta^{dis} E^{max}} \sum_{t'=t-k,t} g_{t'}$$

$$E.\ 31 \quad \delta_t - \frac{1}{\eta^{dis} E^{max}} \sum_{t'=t-k,t} g_{t'} \geq \mu_{1tk} \left(-\frac{1}{\eta^{dis} E^{max}} \sum_{t'=t-k,t} G^{max}\right)$$

$$E.\ 32 \quad \varepsilon_t \leq \mu_{2tk}$$

$$E.\ 33 \quad \sum_{t'=t-k,t} \varepsilon_{t'} - 2 \geq \mu_{3tk}(-2)$$

$$E.\ 34 \quad \mu_{1tk} + \mu_{2tk} + \mu_{3tk} = 2$$

$$E.\ 35 \quad \mu_{1tk}, \mu_{2tk}, \mu_{3tk}, \varepsilon_t \in \{0, 1\}$$

Figure 3-4 shows the cycle's depth calculated for the SoC profile example.

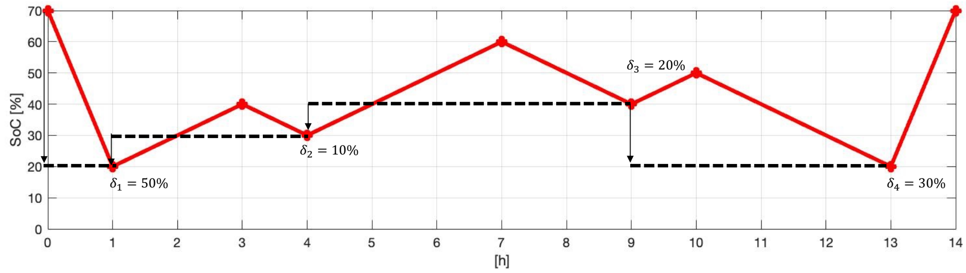

Figure 3-4. Cycle's depth calculation for the SoC profile

3.6 RESOLUTION METHOD

The proposed MLIP model will be solved using mixed-integer programming and the "branch and bound" algorithm in GAMS [29].

Chapter 4. CASE STUDY

This chapter presents the results of the proposed model. The base case solves the economic dispatch with no battery degradation cost using as inputs the national energy and climate plans for Spain (PNIEC) and Portugal (PNEC) for 2030. The first case study performs a sensitivity analysis of the battery's ageing cost over the base case. The second case consists of a sensitivity analysis of the ageing cost linear approximation and the third case analyses the computational results regarding the number of forced cycles and number of segments considered in the linear approximation.

4.1 *INITIAL ASSUMPTIONS*

The model is solved for a time horizon of one week, for the first week of year 2030. This week has been chosen because is the week of the year with the largest variance, allowing to increase the use of the battery to reduce the operation costs of the system.

The initial assumptions considered when solving the model were the following:

- Except for case study 3 the model is solved for the third week of year 2030 since it has the largest demand variance, allowing the battery to increase its use and reduce the system's operation costs and reducing the computational times without compromising the results.
- For thermal technologies, neither startup and shutdown costs nor generation ramps will be considered.
- Instead of a set of installed batteries, only one aggregated average battery is represented by simplicity. This last simplification can be proved to be sensible when only operational decisions are considered. However, when investment decisions are considered, the number and types of batteries to be installed in the long-term might be a key factor since different sizes of the installed power and storage capacity of the

batteries might lead to very different solutions from the point of view of the total system cost minimization.

4.2 BASE CASE

4.2.1 BASE CASE INPUT DATA

4.2.1.1 Electricity Demand

Figure 4-1 presents the weekly demand of the first week year 2030, obtained from [30]. This is the week of year with the largest variance and it is the demand profile that has been used for all the case studies, because, as explained in section 3.1, it provides more information about the behavior of the battery to different demand profiles reducing the computational times without compromising the results.

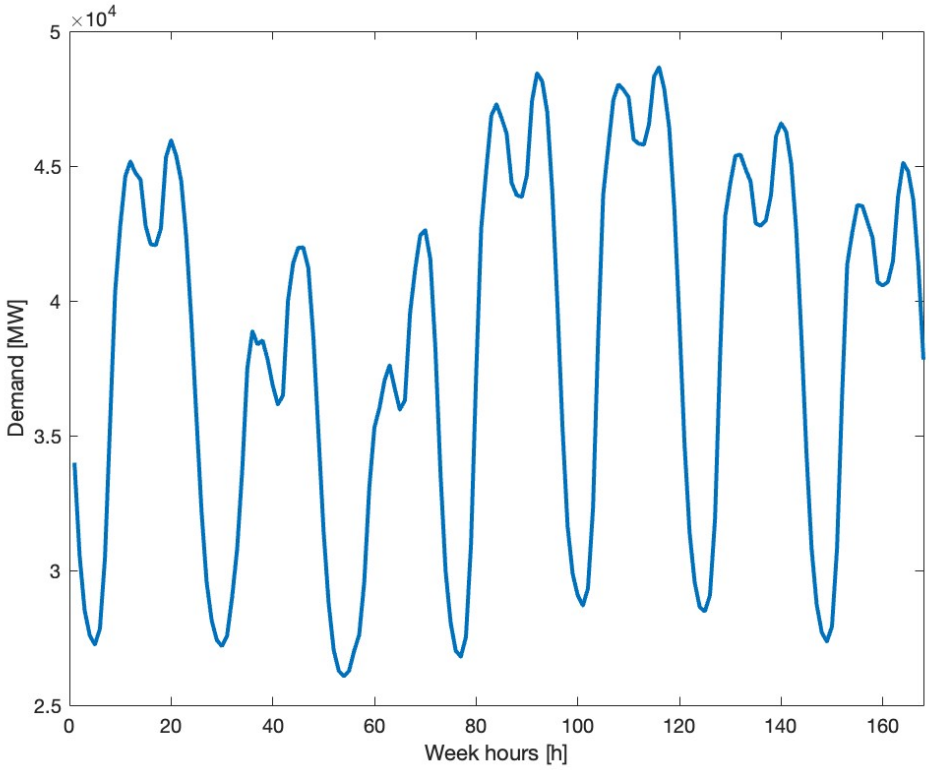

Figure 4-1. Weekly demand used for the case studies

4.2.1.2 Renewable Capacities

The installed capacity for the wind and solar technologies according to [31] is defined in Table 8. The profile shown in Figure 4-2, has been obtained from [30], which includes the production of wind, solar and thermal solar.

Table 8. Renewable energies installed capacity for 2030

Technology	Value	Units
Wind	50,333	GW
Solar	39,181	GW

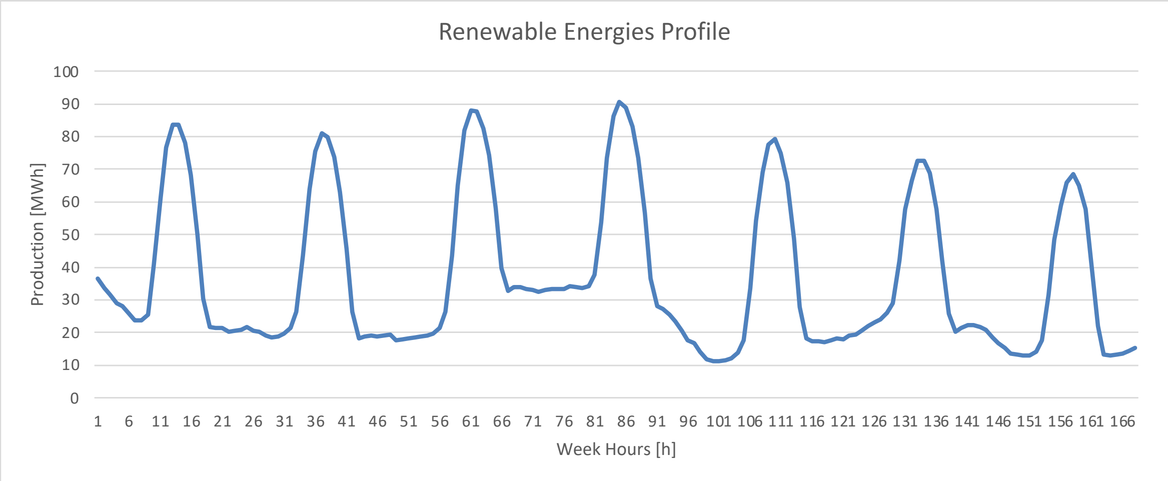

Figure 4-2. Renewable energies profile 2030

4.2.1.3 Stress Function

Equation E. 36 is the stress function used in the model and Figure 4-3 represents the plot of the function.

$$E.\,36 \qquad \Phi(\delta) = (5.24E - 4)\delta^{2.03}$$

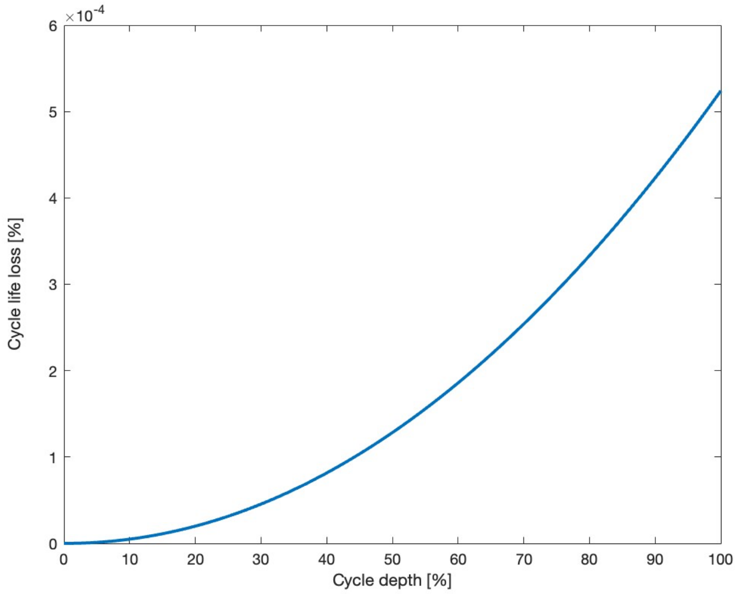

Figure 4-3. Stress function

4.2.1.4 Battery's Parameters

The charge and discharge performance of the battery is of 95%. According to [32] the estimated total amount of energy storage systems installed capacity in 2030 will be of 9 GW. Considering that the battery takes an interval of two hours to completely charge, the maximum SoC is of 18 GWh. The minimum SoC will be of 0 GWh to allow the complete use of the battery. The battery will have an initial level of 9 GWh, this allows the battery to charge or discharge during the first instance according to the needs of the model. The replacement cost is set to be of 151 €/kWh, which is the average price per kWh for lithium-ion batteries according to [33].

The parameters chosen and its units are summarized on Table 9.

Table 9. Battery's parameters

BATTERY PARAMETERS		
Parameter	**Value**	**Units**
Charging performance	95	%
Discharging performance	95	%
Installed power	9	GW
Maximum SoC	18	GWh
Minimum SoC	0	GWh
Maximum discharge and charge power	9	GW
Battery's initial level	9	GWh
Cell replacement cost	151	€/kWh

4.2.1.5 Other Technologies Costs

The costs used for the other technologies present in the model, which include CO_2 prices, fuel gas, nuclear fuel, oil and TTF prices, are summarize in Table 10, which includes the reference from which the price has been obtained.

Table 10. Other technologies costs

BASE CASE PARAMETERS				
		Cost	**Units**	**Reference**
CO2 Costs		93,05	€/TonCO2	[34]
Fuel Costs	**Nuclear**	6	€/MWh_e	[35]
	TTF	48,88	€/MWh_e	[36]

4.2.2 BASE CASE STUDY RESULTS

For the base case study, no degradation costs have been considered to observe the battery's operation without the ageing effect. In addition, three segments linear approximation for the stress function has been considered. A comparison of the results obtained considering and not considering degradation costs is carried out in Case Study 1: Sensitivity Analysis of the Battery Degradation Cost.

Figure 4-4 shows the results obtained for the base case. In Figure 4-4, renewable energies production and battery level is represented on the left axis and the market price is represented on the right axis. The results show that the battery charges while there is a large renewable energy production, and therefore, while the market prices are low. On the other hand, the battery charges while there is a low renewable production, and the market prices are higher. This shows that the battery's model operation is consistent with a real-life battery operation.

This dispatch maximizes the market revenue for the battery energy storage system. The energy storage system charges during renewable generation peaks, when market price is low, and discharges when there a small amount of renewable generation and therefore market price is high. However, it ignores the optimization of the battery's lifespan because the decisions do not take into account the degradation cost.

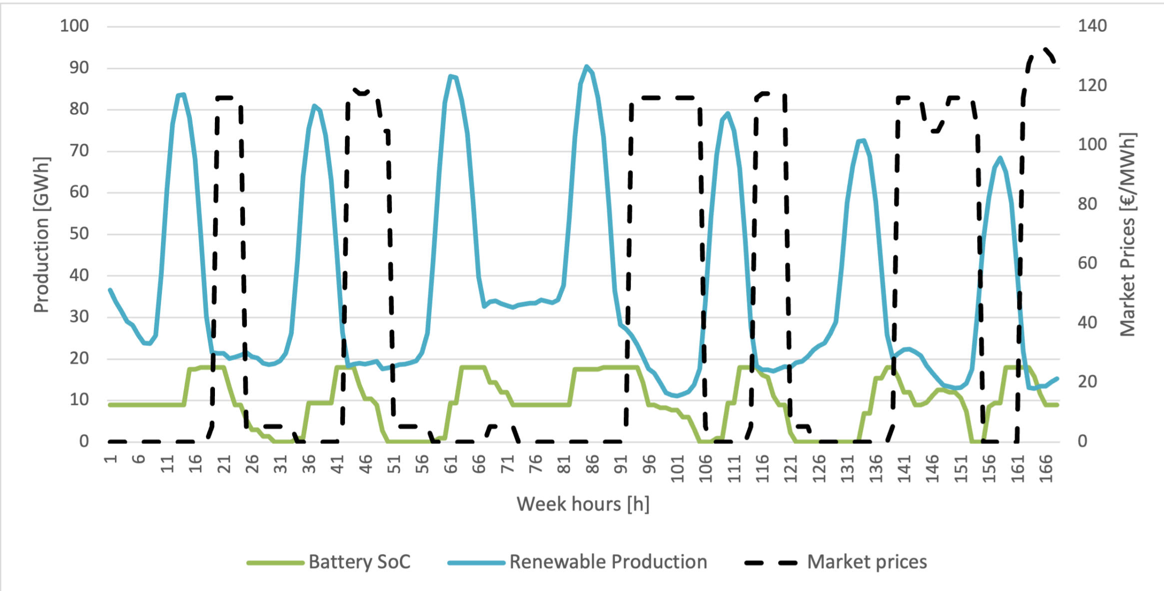

Figure 4-4. Base Case results

4.3 CASE STUDY 1: SENSITIVITY ANALYSIS OF THE BATTERY DEGRADATION COST

This case study compares the battery's operation not considering the degradation cost of the battery and considering it. In addition, case study 1 makes a sensitivity analysis of how the battery management varies with the degradation cost.

4.3.1 DEGRADATION COSTS CASE STUDY 1

As explained in section 4.2.1.4, the replacement cost considered is 151 €/kWh. Three segments linear approximation for the stress function as in the base case has been considered. The stress function Φ is linearly approximated as explained in section 3.3. The replacement cost linearization values using three segments is shown in Table 11. This will be considered the base cost.

Table 11. Replacement cost linearization with three segments

$\Phi(\delta)$	Cost [€]
0,33	8,51
0,67	34,74
1	79,12

For this case study, five subcases have been analyzed considering different degradation costs. The degradation costs considered are shown in Table 12, represented as a percentage of the base costs defined above.

Table 12. Replacement cost for subcases of case 1

Subcase	Percentage of the base cost
1	100%
2	50%
3	75%
4	125%
5	150%

4.3.2 CASE STUDY 1 RESULTS

Figure 4-5 shows a comparison of the battery's operation considering degradation cost, represented in orange, and without considering degradation cost, represented in blue. The figure shows that the degradation cost penalization applied to the objective function, negatively affects the optimal operation of the battery in terms of market revenue for the energy storage system to extent the battery's life and optimize its use. Slower charge and discharge cycles are obtained because of including the degradation cost.

Figure 4-6 shows the sensitivity analysis of the effect of the degradation cost on the battery's operation. As explained in the previous paragraph, the degradation cost affects the battery's operation making the charge and discharge cycles slower to preserve the battery's life. As the price of the degradation cost increases, the charge and discharge cycles decrease their speed. On the contrary, when the degradation cost decreases, the cycles are made faster.

Table 13 shows the number of cycles performed in each case and the objective function result. As shown in the results there is not a significant variation between each of the cases. The degradation cost mainly affects the charge and discharge speed and has a low effect on the battery's SoC profile and the objective function value.

Table 13. Number of cycles and objective function results for case 1

	CASO BASE	BASE PRICE	50% BASE PRICE	75% BASE PRICE	125% BASE PRICE	150% BASE PRICE
Number of cycles	62	66	64	66	65	66
Objective Function [M€]	1389,83	1389,82	1389,02	1389,43	1389,76	1389,52

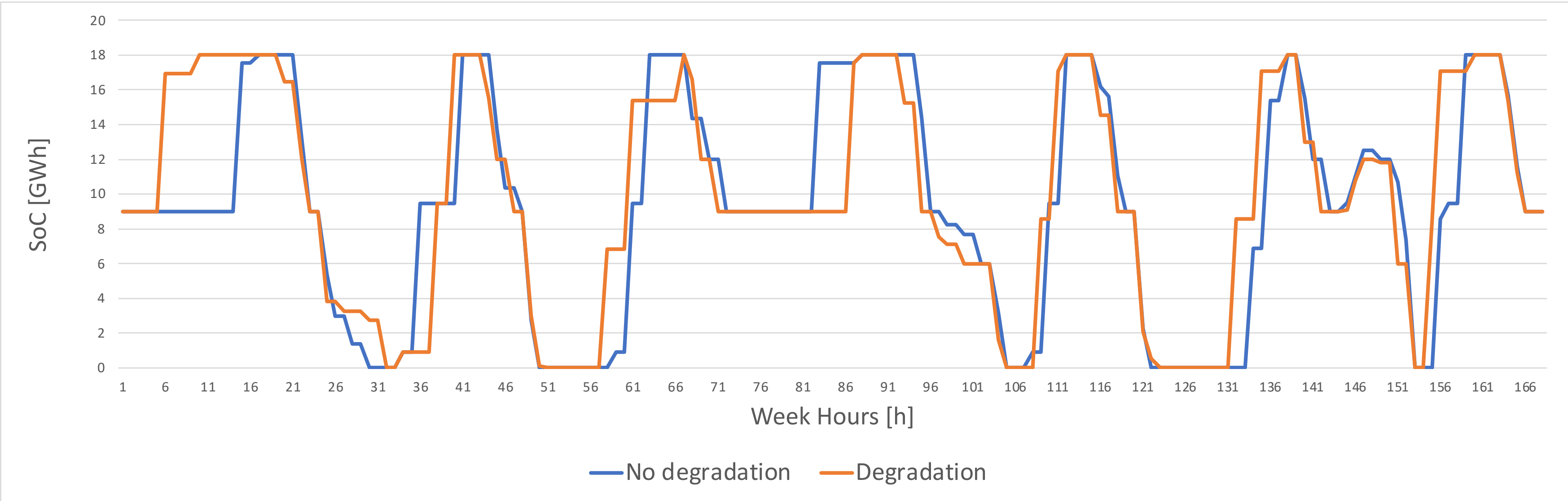

Figure 4-5. Comparison between considering degradation cost and not considering degradation cost

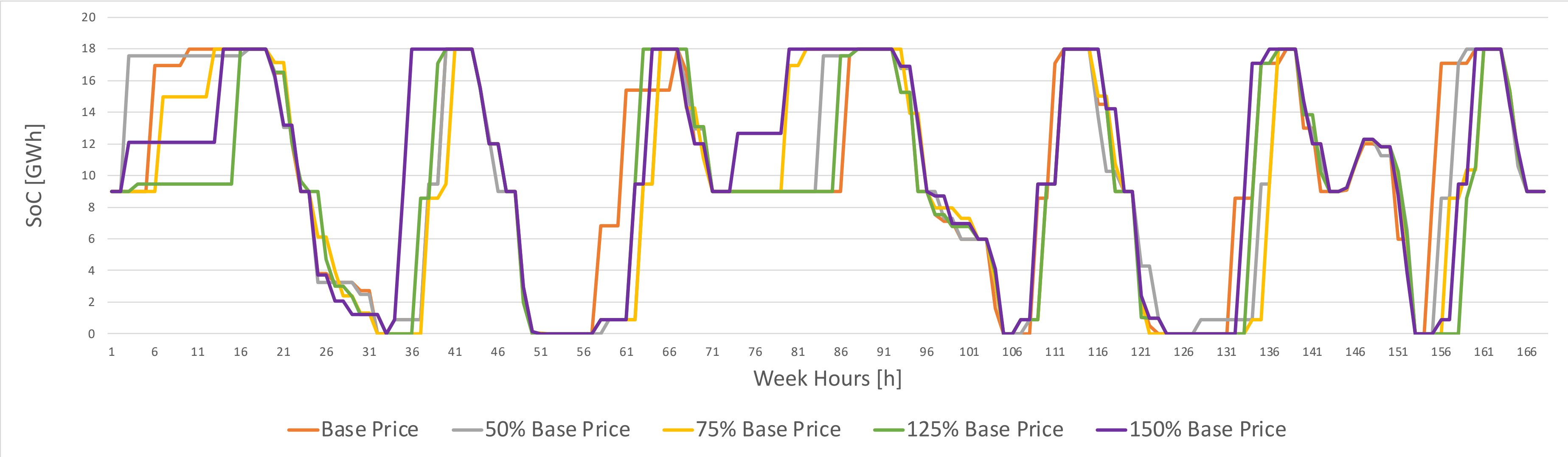

Figure 4-6. Sensitivity analysis of the effect of the degradation cost

4.4 CASE STUDY 2: SENSITIVITY ANALYSIS OF THE DEGRADATION COST LINEAR APPROXIMATION

Case study 2 compares de battery management for piecewise linear cycle aging cost functions with different number of cycle depth segment. For this purpose, the model will be executed varying the number of segments in which the stress function is divided.

4.4.1 DEGRADATION COSTS CASE STUDY 2

As explained in section 4.2.1.4, the replacement cost considered is 151 €/kWh. For case study 2, a sensitivity analysis is carried out to show how a piecewise linear cycle aging cost functions with different number of cycle depth segment affects the model. Five subcases have been carried out increasing the number of segments from 1 to 5. The stress function Φ is linearly approximated as explained in section 3.3. Table 14 shows the linearization values used for each of the subcases.

Table 14. Replacement cost linearization for subcases of case 2

Subcase 1		Subcase 2		Subcase 3		Subcase 4		Subcase 5	
1 segment		2 segments		3 segments		4 segments		5 segments	
$\Phi(\delta)$	Cost[€]	$\Phi(\delta)$	Cost[€]	$\Phi(\delta)$	Cost[€]	$\Phi(\delta)$	Cost[€]	$\Phi(\delta)$	Cost[€]
1	79,12	0,5	19,37	0,33	8,51	0,25	4,74	0,2	3,02
		1	79,12	0,67	34,74	0,5	19,37	0,4	12,32
				1	79,12	0,75	44,12	0,6	28,05
						1	79,12	0,8	50,30
								1	79,12

Figure 4-7 shows how the linearization using different number of segments affects the replacement cost. A cost curve with a greater number of segments is a closer approximation of the actual cycle aging function.

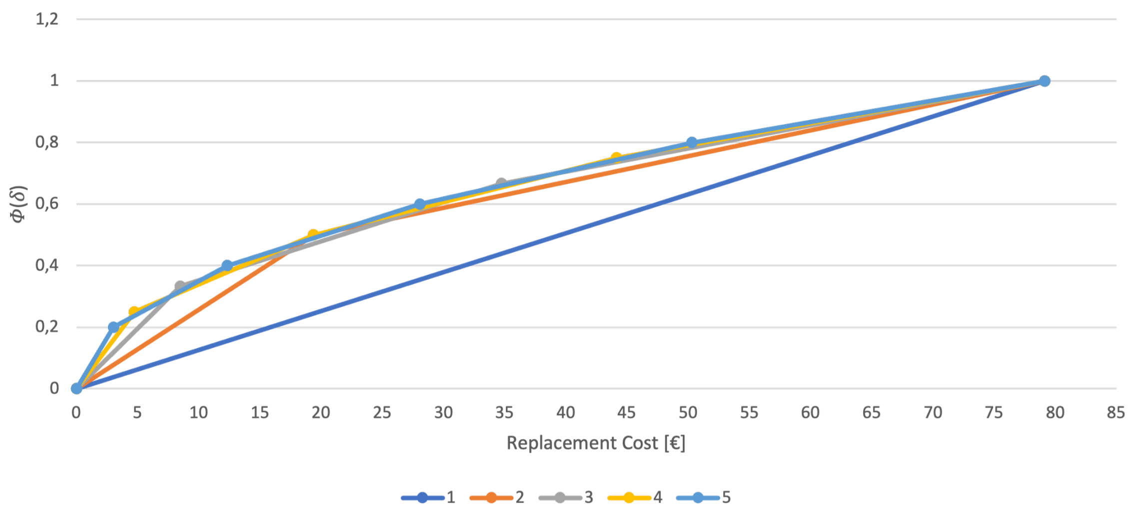

Figure 4-7. Piecewise linear cycle aging cost functions with different number of cycle depth segment

4.4.2 CASE STUDY 2 RESULTS

Figure 4-8 shows the sensitivity analysis of the effect of increasing the number of segments used on the stress function linearization.

When the cycle aging cost is approximated by a single cycle depth segment, the marginal cost of cycle aging remains constant, resulting in an overestimation of the marginal cost of aging and obtaining the most conservative dispatch solution, where the battery only charges and discharges when there is a large price deviation.

Figure 4-9 and Figure 4-10 show the correlation between the market price fluctuation, represented in dashed black, and the battery's state of charge when the cycle aging cost is approximated by a single segment and five segment respectively. It is shown that there is a higher correlation between the market price when approximating the cycle aging cost curve with five segments than with a single segment, meaning the model becomes more sensitive to market price fluctuations as the number of segments applied increases.

It is important to note that between hours 52 and 91 there is a lost in correlation. This is caused by the forced cycles imposed every 24 hours, forcing the battery to carry out a cycle and causing the loss in correlation with the market price.

Table 15 shows the number of cycles performed in each case and the objective function result. As shown in the results there is not a significant variation between each of the cases.

Table 15. Number of cycles and objective function results for case 2

	1	2	3	4	5
Number of cycles	53	61	62	57	59
Objective Function [M€]	1389,97	1389,63	1389,82	1389,32	1389,43

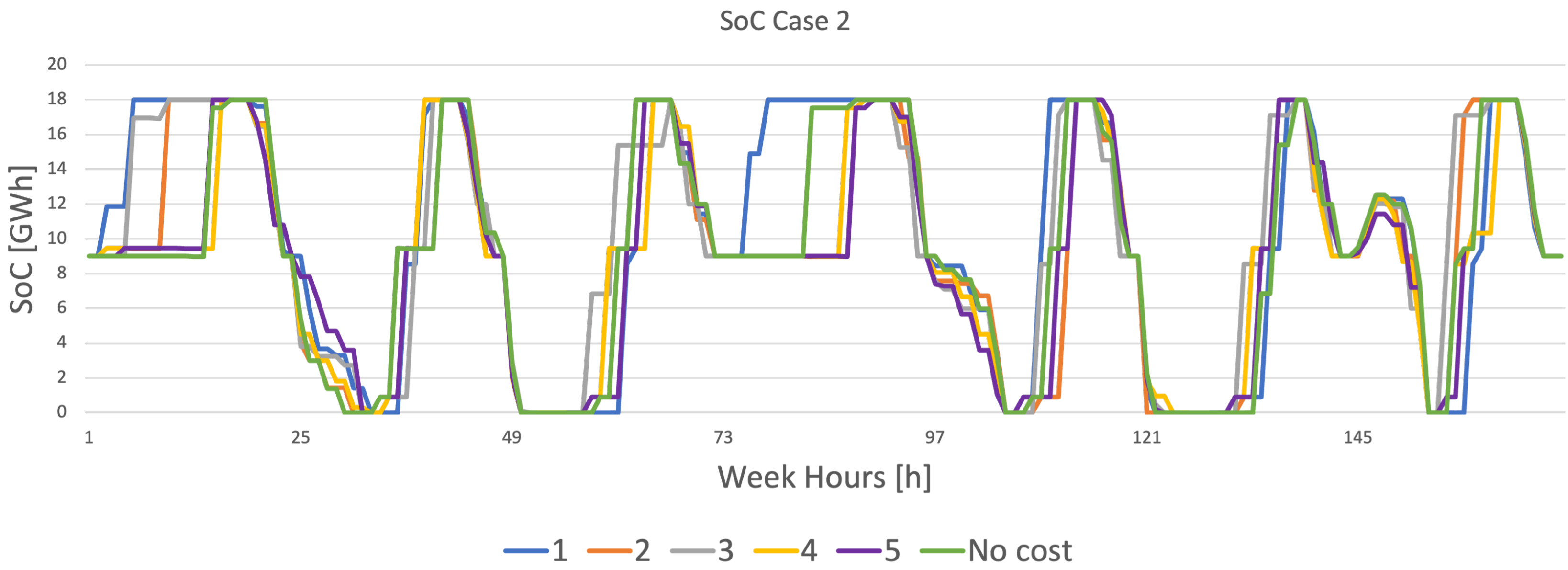

Figure 4-8. Sensitivity analysis of the effect stress function linearization increasing the number of segments

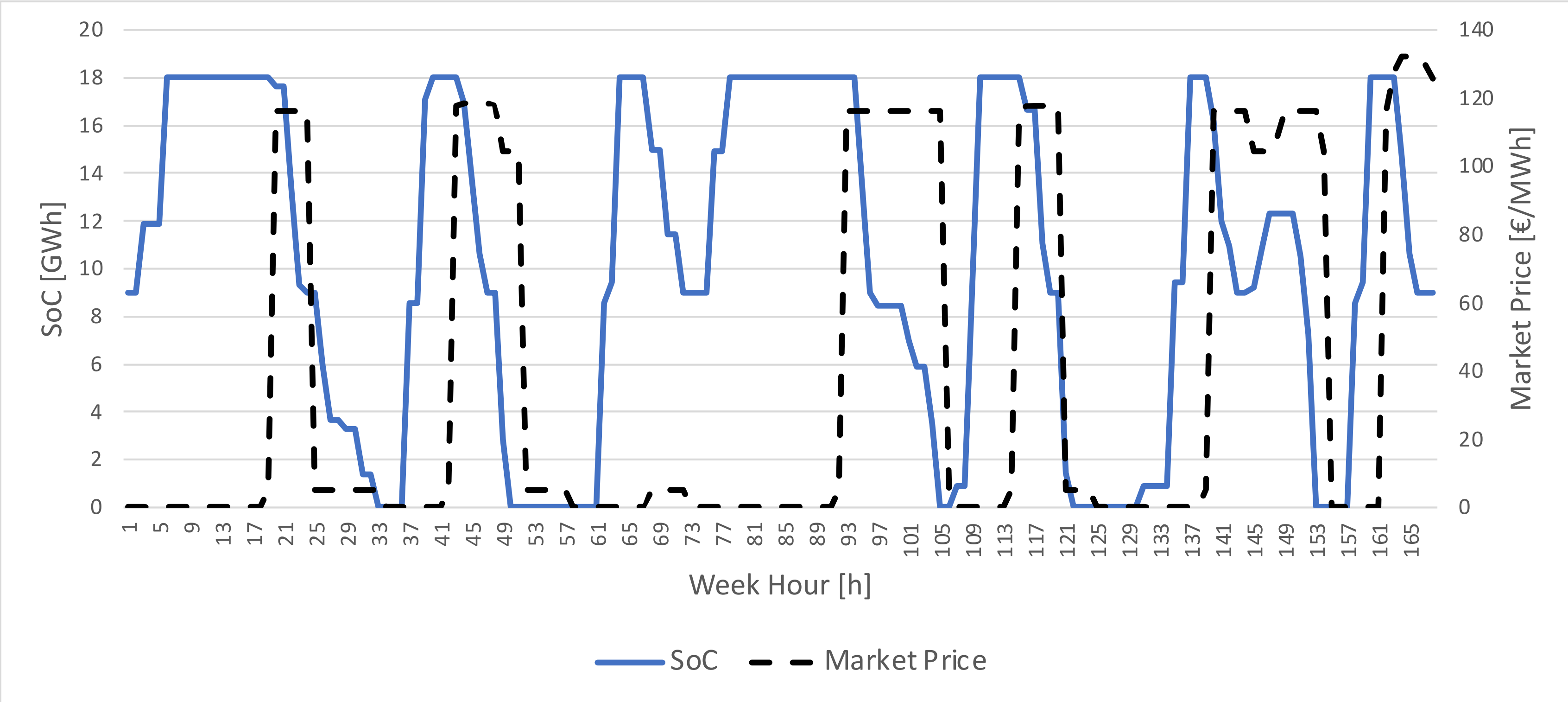

Figure 4-9. Correlation between the market price fluctuation and the state of charge of the battery when the cycle aging cost is approximated by a single segment

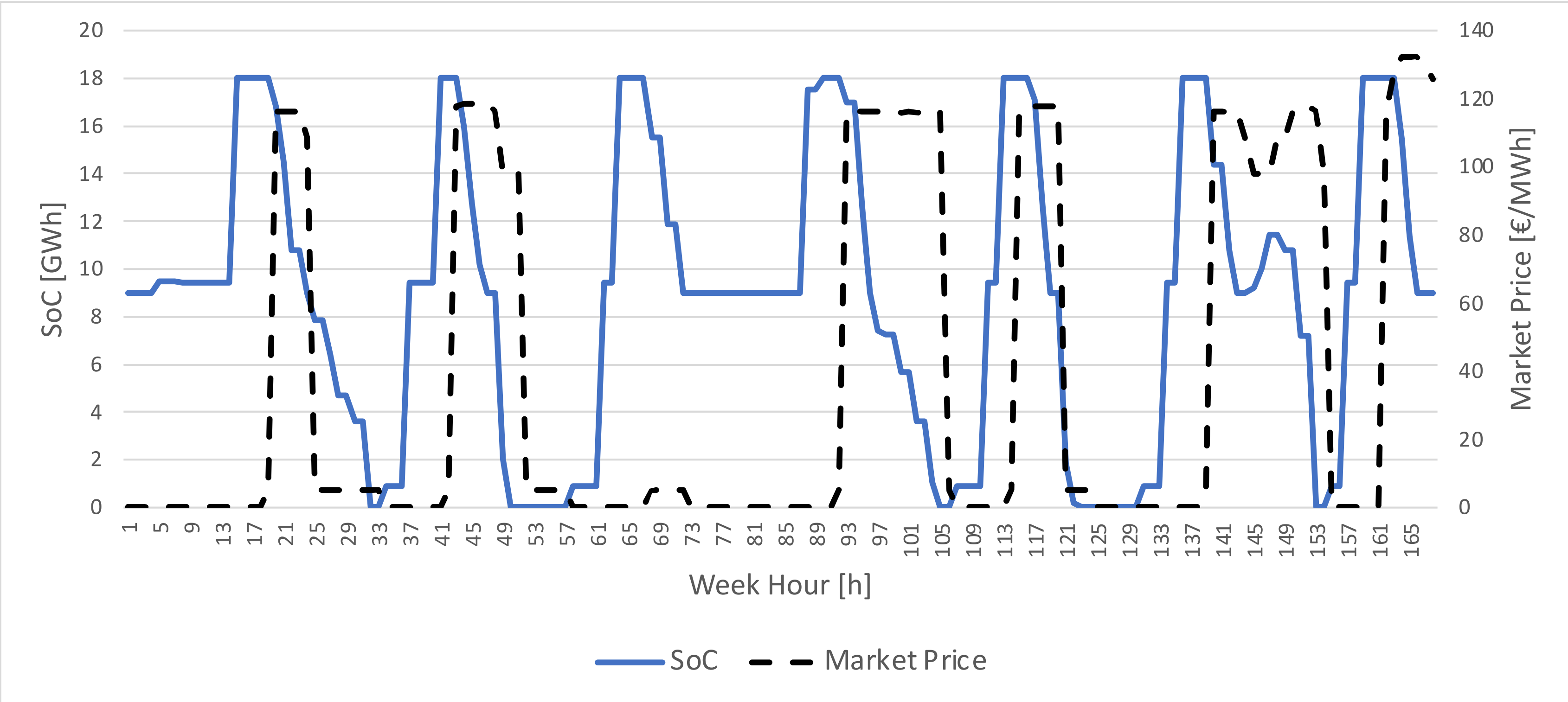

Figure 4-10. Correlation between the market price fluctuation and the state of charge of the battery when the cycle aging cost is approximated by a five segments

4.5 CASE STUDY 3: COMPUTATIONAL RESULTS

Case study 3 compares the computational results regarding the execution times when varying the number of forced cycles and the number segments. In addition, an analysis of the effect on the battery's operation when varying the hours of the forced cycles has been carried out.

The computer used to solve the model is a Huawei MateBook D 14 AMD Ryzen 5 3500U and 8 GB RAM. The computer's operating system is 64-bit, x64-based processor, Windows 11 Home 22H2. The model has been coded with GAMS version 41.4.0 using CPLEX as solver.

4.5.1 FORCED CYCLES

For this subcase study, it has been used the same degradation costs as in the base case of case 1, for a piecewise linear cycle aging cost functions with three cycle depth segments. The replacement costs are shown in Table 11. The time frame remains the same as the rest of the cases, one week.

As explained in subsection 3.1, forced cycles are used to force the battery to have an specific SoC at the end of an specific time frame. These forced cycles have been used to obtain a better representation of the battery's operation reducing the time of optimization.

In this subcase, the computational effect of varying the time frame of forced cycles has been analyzed. In addition, the effect on the battery's operation has been analyzed.

Table 16 shows the computational results obtained when varying the time frame for the forced cycles. It can be observed that as the time of the forced cycles gets higher, it takes a larger computational time.

Table 16. Computational results varying forced cycles

FORCED CYCLE	6H	12H	24H	48H	72H
Execution time [s]	87	196	275	612	1054

Figure 4-11 and Figure 4-12 show the correlation between the market price fluctuation, represented in dashed black, and the time of forced cycles, represented in blue. The figures show that if the time frame is very small, the battery is forced to do the forced cycles, not being able to operate according to the conditions of the system. As the time frame gets bigger, the battery can fulfill the model's conditions. When the forced cycles are set to 6 hours, the battery is not able to follow the market price curve, while as the time frame gets higher, a better fit of the curve is obtained.

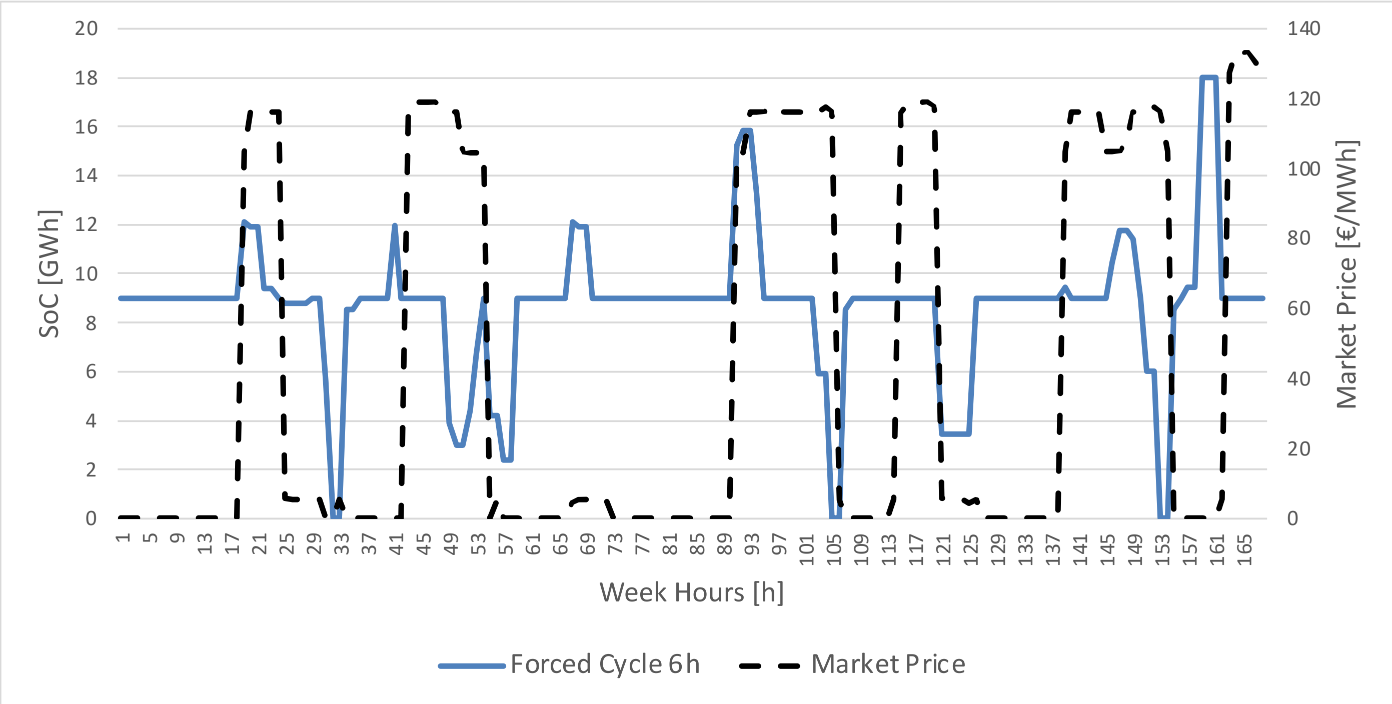

Figure 4-11. Correlation between market price fluctuation and 6-hour forced cycles

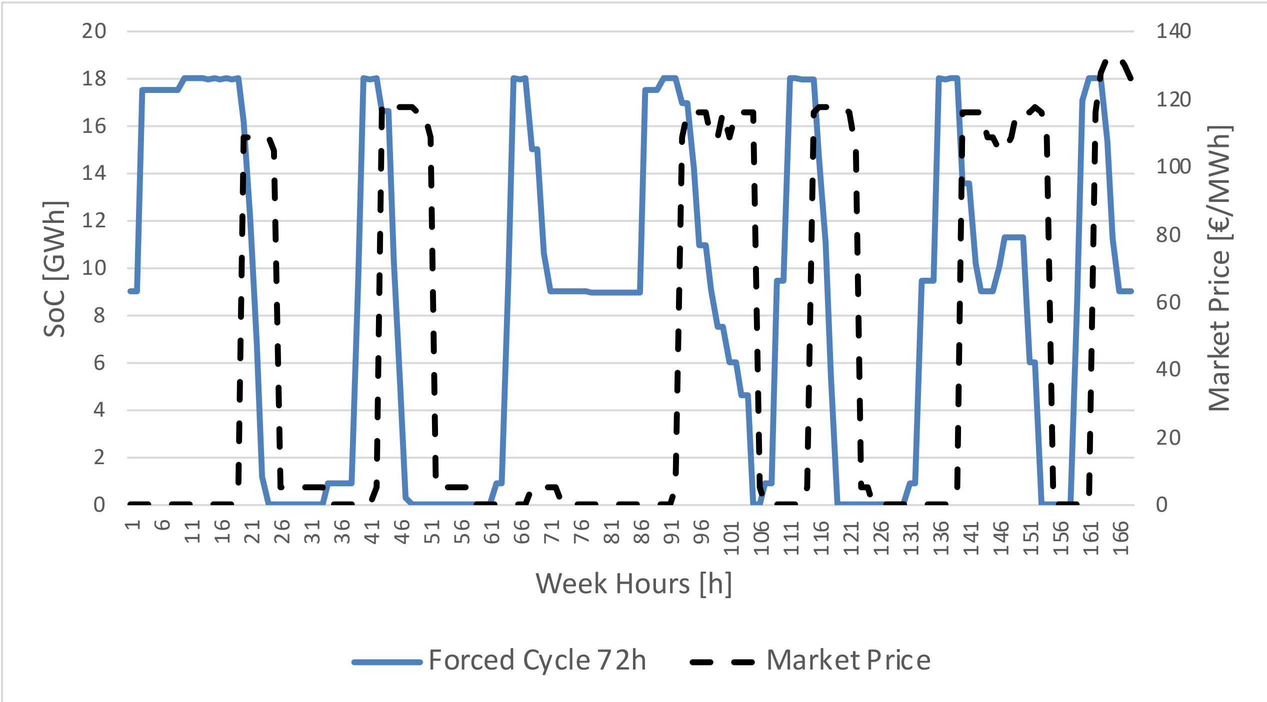

Figure 4-12. Correlation between market price fluctuation and 72-hour forced cycles

4.5.2 NUMBER OF SEGMENTS

For this subcase study, it has been used the same degradation costs as in case 2, for a piecewise linear cycle aging cost function with different cycle depth segments. The replacements costs for each case are shown in Table 14. The time period remains the same as the rest of the cases, one week.

This subcase compares the computational results when varying the number of segments for the piecewise linear cycle aging cost function.

Table 17 shows a comparison of the computational results obtained when varying the number of segments of the cycle aging cost function. As shown in the table, the computational times have a low variation for 2, 3 and 4 segments while for 1 and 5 segments the computational time is longer. Therefore, there is no clear relationship between the number of segments and the execution time.

Table 17. Computational times varying the number of segments of the cost function

NUMBER OF SEGMENTS	1	2	3	4	5
Execution time [s]	332	253	254	287	320

Chapter 5. CONCLUSIONS AND FUTURE DEVELOPMENTS

Energy storage systems have become key components of electricity generation. The growth in interest on this technology over the past two decades is due to the battery technological advancements, the increase in use of renewable energies, infrastructure limitations and changes in the electricity market.

Their capacity to ensure reliability, improve efficiency and integrate renewable energy sources highlights the need to improve the operation and optimization of this systems to reduce its cost and extend their lifespan.

Batteries have a limited of charge and discharge cycles due to degradation, which reduces the battery's energy capacity and lifespan. If this is not considered, this can lead to the battery reaching the end of its lifespan too early with its subsequent economic impact. In addition to economic reasons, environmental sustainability reasons are also key factors to optimize the battery's lifespan due to the rare materials they rely on and their impact on the environment.

This thesis has presented a mixed integer linear mathematical programming model that represents an economic dispatch that includes a degradation cost function to optimize the use of energy storage systems considering charge and discharge cycles as variables of the problem quantified in an endogenously way. To prove its computational efficiency and accuracy three case studies have been carried out.

The first case study compares the battery's operation not considering the degradation cost of the battery and considering it and makes a sensitivity analysis of how the battery management varies with the degradation cost.

The results show that the degradation cost penalization applied to the objective function, negatively affects the optimal operation of the battery in terms of market revenue for the energy storage system to extent the battery's life and optimize its use.

The second case compares de battery management for piecewise linear cycle aging cost functions with different number of cycle depth segment. The results obtained demonstrate that the model becomes more sensitive to market price fluctuations as the number of segments applied increases.

Lastly, the third case compares the computational results regarding the execution times when varying the number of forced cycles and the number segments.

In terms of forced cycles, as the time of the forced cycles gets higher, it takes a larger computational time. However, if the time frame is very small, the battery is forced to do the forced cycles, not being able to operate according to the conditions of the system. For this reason, it is important to find a compromise between these two conditions.

In terms of the number of segments in the degradation cost function, it is key to find the amount of segments needed to correctly represent the degradation cost function without compromising its computational results.

For future developments, the proposed model will be used as an expansion generation model. The model can represent the degradation cost in the objective function as a way to model the replacement cost due to this degradation, making it necessary the installation of new batteries if investment decisions are considered in the long term.

All in all, this thesis proposes a model that easily enables to include the battery's degradation cost, introducing the charge and discharge cycles as variables of the problem and quantifying them in an endogenously way. In addition, the cases studies demonstrate the computational efficiency and accuracy of the model.

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ANNEX I. SUSTAINABLE DEVELOPMENT GOALS

The Sustainable Development Goals (SDG's) are a set of seventeen global goals adopted by the United Nations in September 2015 as part of the 2030 Agenda for Sustainable Development. They represent a universal call to action to end poverty, protect the planet, and ensure people's peace and prosperity by 2030 [36].

This thesis is mainly aligned with four SDG's:

- **SDG 7 "Ensure access to affordable, reliable, sustainable and modern energy".**
  Energy poverty affects to a significant portion of the global population. 13% of the world's population lacks access to modern and reliable energy services especially affecting people in rural areas and in low-income communities, making it difficult for them to meet their basic needs and improve their living conditions [38].
  By optimizing energy storage systems, the integration of renewable energy sources such as solar and wind into the grid are enhanced, making clean and sustainable energy more accessible and affordable.

Figure 0-1. SDG 7 "Ensure Access to affordable, reliable, sustainable and modern energy"

- **SDG 11 "Make cities inclusive, safe, resilient and sustainable".**
  More than 50% of the world's population live in cities, considered drivers of economic growth and major contributors of the global GDP [37].

Energy storage systems support the development of smart grids and sustainable energy management, promoting more resilient, sustainable, and cleaner cities.

Figure 0-2. SDG 11 "Make cities inclusive, safe, resilient, and sustainable"

- **SDG 12 "Ensure sustainable consumption and production patterns".**
  Unsustainable patterns can cause triple planetary crises involving climate change, biodiversity loss and pollution threatening human well-being. Goal 12 main target is to improve resource efficiency, reduce waste and pollution, and shape a new circular economy [37].
  Optimizing the management of energy storage systems which help extending their lifespan, contributes to a more efficient energy consumption, reducing waste and promoting more sustainable production technologies.

Figure 0-3. SDG 12 "Ensure sustainable consumption and production patterns"

- **SDG 13 "Take urgent action to combat climate change and its impact"**
  Due to the increase in concentrations of global greenhouse gases together with the rise of the Earth's temperature, taking urgent action to combat climate change and

its devastating impacts has become a key goal for the 2030 Agenda for Sustainable Development [37].

Energy storage systems provide more stability to the grid, allow to manage the fluctuations of renewable energies technology generation, reducing the use of fossil fuels and contributing to the mitigation of climate change.

Figure 0-4. SDG 13 "Take urgent action to combat climate change and its impact"

ANNEX II. LOGICAL PREPOSITIONS MODEL METHODOLOGY

In this annex the methodology used to transform logical implications into mathematical constraints with new binary variables will be explained. For this purpose, a generic logical implication is explained first, and then this methodology is applied to the logical implications used in the model.

Equation E. 37 is a logical implication that states that if two constraints g(x) and h(x) are fulfilled, then another constrained f(x) should be fulfilled.

$$E.\ 37 \quad \underbrace{If\ g(x) \leq 0\ and\ h(x) > 0}_{\text{A}} \rightarrow \underbrace{f(x) \leq 0}_{\text{B}}$$

To transform a logical implication into mathematical constraints with binary variables we have to apply first the Morgan's Law. According to Morgan's Law, showed in equation E. 38, if A implies B, is equivalent to it is B or no A.

$$E.\ 38 \quad A \rightarrow B \leftrightarrow B\ or\ not\ A$$

If we apply Morgan's Law to equation E. 37, equation E. 39 is obtained. In this way, each "or" condition has its corresponding binary variable that allows to activate or desactivate the constraint.

$$E.\ 39 \quad \underbrace{f(x) \leq 0}_{\text{B}}\ or\ \underbrace{g(x) > 0\ or\ h(x) \leq 0}_{\text{no A}}$$

In optimization problems, the greater than (>) or less than (<) sings cannot be used so they must be replaced by greater-than or equal (≥) or less-than or equal(≤) sings. To do that, we assume a small error ε, where ε is a small positive parameter. Equation E. 39 leads to Equation E. 40 with only greater-than or equal or less-than or equal sings.

$$E.\ 40 \quad f(x) \leq 0 \ or \ g(x) \geq \varepsilon \ or \ h(x) \leq 0$$

Then each "or" condition is replaced by a constraint activated by a binary variable and an upper or lower bound according to their sing. If the sing is lower or equal, then an upper bound is used, if the sing is greater or equal, a lower bound is used. Equations E. 41, E. 42 and E. 43 shows the result of applying this procedure to equation E. 40.

$$E.\ 41 \quad f(x) \leq \mu_1 \cdot \overline{f}$$

$$E.\ 42 \quad g(x) - \varepsilon \geq \mu_2 \cdot (\underline{g} - \varepsilon)$$

$$E.\ 43 \quad h(x) \leq \mu_3 \cdot \overline{h}$$

$\overline{f}$, $\underline{g}$ and $\overline{h}$ being the upper, lower and upper bounds of f(x), g(x) and h(x) respectively.

Since one of the previous constraints must get active, and additional constrain E. 44 must be added to force one of the binary variables to be zero.

$$E.\ 44 \quad \mu_1 + \mu_2 + \mu_3 = 2$$

The final transformation of the logical implication into mathematical constrains consist of E. 41, E. 42, E. 43 and E. 44

Now this general methodology is applied specifically to the logical implications used in the model.

Equation E. 45 is the logical implication used to count the number of cycles. If the battery is discharging at time t-1 and it stops discharging at time t, then the binary variable ε_t should get active indicating the end of a discharge cycle. Equations E. 46 and E. 47 use the methodology described before.

$$E.\ 45 \quad If\ g_{t-1} > 0\ and\ g_t \leq 0 \rightarrow \varepsilon_t = 1$$

$$E.\ 46 \quad \varepsilon_t = 1\ or\ g_{t-1} \leq 0\ or\ g_t > 0$$

$$E.\ 47 \quad \varepsilon_t = 1\ or\ g_{t-1} \leq 0\ or\ g_t \geq \varepsilon$$

The final constraints are shown in equations E. 48, E. 49 and E. 50. In this case, no additional binary variable is needed to activate ε_t because it will only get active if the other two binary variables are not active.

$$E.\ 48 \quad g_{t-1} \leq \rho_{1t}(E^{max})$$

$$E.\ 49 \quad g_t - \varepsilon \geq \rho_{2t}(-\varepsilon)$$

$$E.\ 50 \quad \rho_{1t} + \rho_{2t} = 1 + \varepsilon_t$$

Depending on the model, sometimes is necessary to add the opposite logical implication, shown in equation E. 51.

$$E.\ 51 \quad If\ \varepsilon_t = 1 \rightarrow g_{t-1} > 0\ and\ g_t \leq 0$$

The methodology applied is the same as the one applied to the previous constraints; however, no additional binary variables are needed because they are associated to the activation of the same variables. Equations E. 52 and E. 53 show the remaining constraints.

$$E.\ 52 \quad g_{t-1} - \varepsilon \geq (1 - \varepsilon_t)(-\varepsilon)$$

$$E.\ 53 \quad g_t \leq (1 - \varepsilon_t)(E^{max})$$

For the logical implication related to the definition of the cycle's depth, shown in equation E. 54, the same methodology is applied, leading to equation E. 55.

$$E.\ 54 \qquad If\ \varepsilon_t = 1\ and\ \sum_{t'=t-k,t} \varepsilon_{t'} = 1 \rightarrow \delta_t \geq \frac{1}{\eta^{dis} E^{max}} \sum_{t'=t-k,t} g_{t'}$$

$$E.\ 55 \qquad \delta_t \geq \frac{1}{\eta^{dis} E^{max}} \sum_{t'=t-k,t} g_{t'}\ or\ \varepsilon_t \leq 0\ or\ \sum_{t'=t-k,t} \varepsilon_{t'} \geq 2$$

Equations E. 56, E. 57, E. 58 and E. 59 show the final constraints equivalent to implication E. 54 when applied the general methodology described at the beginning of this section.

$$E.\ 56 \qquad \delta_t - \frac{1}{\eta^{dis} E^{max}} \sum_{t'=t-k,t} g_{t'} \geq \mu_{1tk} \left(-\frac{1}{\eta^{dis} E^{max}} \sum_{t'=t-k,t} G^{max} \right)$$

$$E.\ 57 \qquad \varepsilon_t \leq \mu_{2tk}$$

$$E.\ 58 \qquad \sum_{t'=t-k,t} \varepsilon_{t'} - 2 \geq \mu_{3tk}(-2)$$

$$E.\ 59 \qquad \mu_{1tk} + \mu_{2tk} + \mu_{3tk} = 2$$