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POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

Development of an Optimized Life Cycle Assessment Method for the Evaluation of Time-Variant Systems

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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Cette thèse intitulée :

Development of an Optimized Life Cycle Assessment Method for the Evaluation of time-Variant Systems

présentée par **Hassana ELZEIN**

en vue de l'obtention du diplôme de *Philosophiæ Doctor*

a été dûment acceptée par le jury d'examen constitué de :

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DEDICATION

To my grandparents, parents and beloved sister..

Abboudeh, I did it for you!

"C'est une folie d'haïr toutes les roses parce qu'une épine vous a piqué, d'abandonner tous les rêves parce que l'un d'entre eux ne s'est pas réalisé, de renoncer à toutes les tentatives parce qu'on a échoué..

C'est une folie de condamner toutes les amitiés parce qu'une vous a trahi, de ne croire plus en l'amour juste parce qu'un d'entre eux a été infidèle, de jeter toutes les chances d'être heureux parce que quelque chose n'est pas allé dans la bonne direction.

Il y aura toujours une autre occasion, un autre ami, un autre amour, une force nouvelle. Pour chaque fin, il y a toujours un nouveau départ.."

Le Petit Prince
Antoine de Saint-Exupéry

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RÉSUMÉ

Le secteur d'énergie subit actuellement des changements structurels visant à réduire ses impacts environnementaux et d'atteindre les objectifs d'atténuation du changement climatique des Nations Unies. À l'échelle mondiale, les centrales à combustibles fossiles sont en cours de déclassement, des sources d'énergie renouvelables sont installées et de nouvelles technologies, telles que les systèmes de stockage d'énergie (SSE), sont progressivement déployées. La conception, l'optimisation et la gestion des réseaux futurs nécessitent une compréhension détaillée des législations et des impacts environnementaux pour permettre un déploiement optimal et des choix opérationnels optimaux.

Les impacts environnementaux de différentes technologies de production d'énergie sont évalués à l'aide de la méthode d'analyse du cycle de vie (ACV) afin de permettre une prise de décision robuste en ce qui concerne la conception des réseaux futurs et d'établir des politiques et des réglementations adéquates.

Dans le réseau futur, les systèmes de stockage d'énergie tels que les batteries à grande échelle devraient constituer un élément essentiel du paradigme production-stockage-fourniture. La phase d'utilisation de ces technologies doit être évaluée avec précision pour comprendre leurs impacts potentiels sur l'environnement et évaluer leurs avantages. Les méthodes actuelles d'ACV ne permettent pas d'évaluer les SSE en raison, entre autres, de la fausse représentation de l'intrinsèque nature de ces systèmes variable dans le temps et de l'omission des contraintes de réseau.

L'objectif général de ce travail doctoral est de développer une méthode d'ACV permettant d'évaluer et de comparer les impacts environnementaux potentiels de l'opération du SSE dans les réseaux électriques. En outre, la méthode développée a été conçue pour 1) intégrer la variabilité temporelle du SSE pour améliorer l'analyse de ses impacts environnementaux, 2) intégrer les coûts externes de la production d'électricité dans l'estimation des impacts évités de l'opération du SSE, et 3) élaborer un cadre d'évaluation à court terme des réseaux électriques déployant un SSE.

Tout d'abord, une nouvelle méthode d'évaluation du cycle de vie intégrant un algorithme d'optimisation a été développée pour refléter le fonctionnement dynamique du SSE et mettre en évidence son rôle dans le réseau électrique. Les impacts environnementaux évités de la phase d'utilisation du SSE ont été estimés et comparés aux résultats d'autres méthodologies d'évaluation

du SSE. Les résultats ont mis en évidence les réductions potentielles des émissions de gaz à effet de serre (GES) provenant de la production d'électricité après l'optimisation du réseau et l'inclusion d'un SSE. L'estimation des impacts évités a été améliorée lorsque la méthode d'analyse a pris en compte la variabilité temporelle du fonctionnement des ESS, ce qui a permis de mieux comprendre le profil environnemental du système de stockage tout au long de son cycle de vie.

Ensuite, différentes catégories d'impacts environnementaux ont été considérées. Les impacts sur la santé humaine et la qualité des écosystèmes ont également été introduits dans l'optimisation de la production d'électricité, car la prise en compte de plusieurs catégories d'impact modifierait le fonctionnement des différentes technologies du réseau. Par conséquent, les sources alimentant le SSE seraient différentes et influeraient les impacts évités de son fonctionnement. Les résultats ont mis en évidence le rôle du SSE dans le réseau optimisé. Les impacts évités durant la phase d'utilisation du SSE étaient plus importants lorsque le réseau optimisé prenait en compte les dommages pour la santé humaine et la qualité de l'écosystème, en plus du changement climatique. Ainsi, la prise en compte de catégories d'impact supplémentaires lors de la modélisation du réseau électrique améliore la compréhension du fonctionnement du SSE et l'estimation de ses impacts évités.

Finalement, une évaluation prospective du réseau électrique a été réalisée à l'aide de notre méthode développée. La production électrique optimisée a été modélisée en tenant compte des plans énergétiques et des objectifs d'émission à court terme (c'est-à-dire cinq ans). Plusieurs scénarios ont été comparés pour évaluer les conséquences environnementales de différentes décisions : production accrue à partir d'énergies renouvelables, démantèlement des centrales au charbon, déploiement d'un SSE et installation de centrales nucléaires. Les principales conclusions ont permis de comparer des solutions alternatives et de souligner le rôle du SSE dans la substitution de certains combustibles fossiles, réduisant ainsi les émissions de GES.

Ce projet de recherche a permis de résoudre plusieurs problèmes liés à l'évaluation environnementale des systèmes de stockage d'énergie dans les réseaux électriques. Le cadre méthodologique développé a amélioré la modélisation, l'analyse et la comparaison de la phase d'utilisation du SSE et peut donc être utilisé pour aider les décideurs politiques et les opérateurs de réseaux dans leurs décisions. Malgré ses avantages, l'application de la nouvelle méthode est limitée

par la disponibilité des données, les choix méthodologiques faits pendant l’analyse et l'exclusion de catégories d'impact supplémentaires telles que l'épuisement des ressources.

ABSTRACT

The power sector is undergoing structural changes to reduce its environmental impacts and meet United Nation climate change mitigation goals. Globally, fossil fuel power plants are being decommissioned, renewable energy sources are installed and new technologies such as Energy Storage Systems (ESSs) are progressively deployed. The design, optimization, and management of future grids require a detailed understanding of legislation, and environmental impacts to drive optimal deployment and operational choices.

Environmental impacts of different power generation technologies are assessed using the Life Cycle Assessment (LCA) method to drive robust decision-making vis-à-vis future grid designs and to establish policies and regulations.

In the future grid, energy storage systems such as large-scale batteries are expected to be an essential part of the generation-storage-supply paradigm. The use phase of such technologies needs to be accurately evaluated to understand their potential environmental impacts and assess their benefits. Present LCA methods fall short to assess ESSs due to, among others, the misrepresentation of the intrinsic time-variable nature of these systems and the omission of the grid constraints.

The overall objective of this Ph.D. work was to develop an LCA method that evaluates and compares potential environmental impacts from ESS operation in power grids. In addition, the developed method was devised to **1)** incorporate ESS temporal variability for an enhanced assessment of its environmental impacts, **2)** integrate external costs of electricity generation in the estimation of avoided impacts from ESS operation, and **3)** elaborate a framework to assess power grids deploying an ESS in the short-term.

First, a new life cycle assessment method integrating an optimization algorithm was developed to reflect the dynamic operation of ESS and highlight its role in the power grid. The avoided environmental impacts from the ESS use phase were estimated and compared to the findings from other ESS evaluation methodologies. Results emphasized the potential greenhouse gas emission reductions from the grid operation after the optimization and inclusion of an ESS. Estimation of avoided impacts was enhanced when the analysis method accounted for the temporally variable

operation of ESSs, allowing a better understanding of the environmental profile of the storage system throughout its entire life cycle.

Next, different environmental impact categories were considered. Impacts on human health and ecosystem quality were also introduced in the optimization of the electricity generation process since the consideration of several impact categories would alter the operation of the different technologies in the grid. Consequently, the sources feeding the ESS would differ and affect the avoided impacts from its operation. Results highlighted the role of the ESS in the optimized electric grid. The avoided impacts from the ESS operation were more important when the optimized grid considered the damages to human health and ecosystem quality in addition to climate change. Thus, considering additional impact categories when modelling the power grid improves the understanding of the ESS operation and the estimation of its avoided impacts

Finally, a prospective assessment of the power grid was performed using our developed method. The optimized electricity generation was modelled while accounting for the energy plans and emission targets in the short-term (i.e. five years). Different scenarios were compared to assess the environmental consequences of various decisions: increased generation from renewables, decommissioning of coal power plants, deployment of ESS and installation of nuclear power plants. The main findings allowed the comparison of alternative solutions and emphasized the role of ESS in substituting some fossil fuels, consequently reducing GHG emissions.

This research project answered several limitations related to the environmental assessment of energy storage systems in power grids. The developed methodological framework improved modelling, evaluation, and comparison of the ESS use phase and can be therefore used to support policymakers and grid operators in their decisions. Despite its advantages, the application of the new method is constrained by data availability, the methodological choices made throughout the analysis, and the exclusion of additional impact categories such as resource depletion.

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LIST OF SYMBOLS AND ABBREVIATIONS

A-LCA	Attributional Life Cycle Assessment
BESS	Battery Energy Storage System
C-LCA	Consequential Life Cycle Assessment
CASES	Cost Assessment of Sustainable Energy Systems
CC	Climate Change
CO_2	Carbon Dioxide
D-LCA	Dynamic Life Cycle Assessment
DALY	Disability Adjusted Life Years
EF	Emission Factor
EoL	End of Life
EPA	Environmental Protection Agency
EQ	Ecosystem Quality
ESA	Environmental Scenario Analysis
ESM	Energy System Model
ESS	Energy Storage System
EVs	Electric Vehicles
F.U.	Functional Unit
GHG	Greenhouse Gas
HH	Human Health
ISO	International Organization for Standardization
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment

Li-ion	Lithium-ion
MJ	Megajoules
NG	Natural Gas
NREL	National Renewable Energy Laboratory
O-C-LCA	Optimized-Consequential Life Cycle Assessment
PDF/m^2/yr	Potentially Disappeared Fraction of species in a specific area for a specific time
PHS	Pumped Hydro Storage
R	Resources
RES	Renewable Energy Sources
RTE	Réseau de Transport d'Électricité

LIST OF APPENDICES

CHAPTER 1 INTRODUCTION

1.1 Background

The energy sector is a major contributor to climate change (IEA, 2018). In 2014, it was responsible for 49% of the total greenhouse gas (GHG) emissions worldwide (Ritchie & Roser, 2018). Nowadays, industrialized societies became increasingly reliant on electricity as a versatile energy carrier (Raugei & Leccisi, 2016). The pursuit of sustainable energy alternatives is becoming a critical demand due to the depletion of fossil fuels and the need to meet the ever-growing energy demand (Larcher & Tarascon, 2015). The major challenge, encountered by energy producers, policymakers and society as a whole, is therefore to preserve the current standard of living while meeting environmental impact reduction targets (Martín-Gamboa, Iribarren, García-Gusano, & Dufour, 2019; Padey, Girard, Le Boulch, & Blanc, 2013).

The energy sector must undergo a transformative change to provide reliable and affordable energy as per the United Nations sustainable development goals (UN, 2016) and to meet the objectives of the Paris agreement (UN, 2015). Governments are urged to strengthen their climate policies (Frischknecht et al., 2018) and perform sensible planning with respect to generation, distribution, and consumption (Gómez, Dopazo, & Fueyo, 2016). Energy strategies should ensure the availability of electricity while reducing the hazardous effects on the environment and societies (Gómez et al., 2016; Hellweg, S. & Mila i Canals, 2014; Ouedraogo, 2017). Policymakers are interested in better understanding the environmental impacts of their decisions to evaluate new technologies, identify the most profitable sectors for investments and implement new policies for GHG emission reduction (Hellweg, S. & Mila i Canals, 2014; REN21, 2019; Sandén & Karlström, 2007). These policies focus on decommissioning of conventional power plants, promoting the strong growth of renewable energy sources and deploying novel and efficient energy storage systems (ESS) to transform the national power generation mixes (Larcher & Tarascon, 2015; Martín-Gamboa et al., 2019).

There is, therefore, an urgent need to accurately evaluate the potential impacts of the produced electricity (Hellweg, S. & Mila i Canals, 2014; Padey et al., 2013). Decision-makers must assess the available technologies to reduce their environmental damages (Rebitzer, G. et al., 2004),

identify the most polluting steps (Ekvall, Tomas & Weidema, 2004), compare alternatives (Rebitzer, Gerald et al., 2004) and foster energy transition (Blanc, 2015).

Life Cycle Assessment (LCA) is a standardized decision-making method used to evaluate the environmental aspects and potential impacts of products (ISO, 2006a, 2006b). It is applied to examine the effectiveness of planned strategies, estimate the environmental performances of emerging technologies, and analyze systems from cradle-to-grave (Blanc & Beloin-Saint-Pierre, 2013; Curran, 1996). That is, all the life cycle stages are investigated, including raw material acquisition, manufacturing, use phase, and end-of-life processes. LCA helps in better understanding the sources of impacts and in avoiding their displacement between the different life cycle steps.

LCA has been widely applied to study the energy sector. It helped grid-operators in evaluating the various scenarios and technologies, assisted decision-makers in drafting new strategies and supported governments in setting and assessing their targets and emission limits (e.g. (Asdrubali, Baldinelli, D'Alessandro, & Scrucca, 2015; Gagnon, Belanger, & Uchiyama, 2002; Meier, 2002; Turconi, Boldrin, & Astrup, 2013)). Despite its numerous advantages, LCA sometimes lacks a clear representation of system dynamics when modelling and evaluating the use phase of new technologies (Turconi, Tonini, Nielsen, Simonsen, & Astrup, 2014).

Misrepresentation of the operation of time-variant systems complicates their environmental impact assessment, limits the communication of results and can engender inappropriate decisions and misleading conclusions (Collinge, Landis, Jones, Schaefer, & Bilec, 2012; Sandén & Karlström, 2007; Weidema, Bo Pedersen, 2000). For the evaluation of electricity generation, the variability of operation of the different technologies needs to be properly incorporated in the applied LCA models. Hence, to improve both the quality and accuracy of the findings and better support decision-makers, three main questions need to be addressed: i) how to incorporate the time-variant aspect of new technologies, such as energy storage systems, in LCA, ii) how to incorporate the cost of energy in the environmental evaluation of new technologies, and iii) how to assess the environmental impacts of power grids including new technologies in the short-term.

The work presented in this thesis attempts to address the aforementioned questions and incorporate the system dynamics in a new method to properly assess the use phase of new technologies in the

power sector. As such, the aim of this research is to evaluate and compare the potential environmental impacts of energy storage systems in electric grids.

1.2 Structure of the thesis

The thesis is composed of nine chapters, starting with a general introduction of the subject and a presentation of the thesis structure. **Chapter 2** presents a concise literature review of the following subject matters 1) Electricity generation, 2) Energy storage systems, 3) Life cycle assessment, 4) External costs of energy and 5) Future grid assessment, in order to familiarize the reader with the subject of this thesis. At the end of this chapter, the demerits of the present methodologies are identified, and the problem addressed is clearly stated. **Chapter 3** presents the research question, hypothesis, and the objective of the thesis. In this chapter, the general methodological framework is detailed for a better understanding of the thesis work, data and conclusions. **Chapter 4** introduces the core of the thesis and describes subsequent chapters. **Chapters 5-7,** present the main outcomes of the thesis in the form of published and submitted manuscripts. In each chapter, the most important findings are demonstrated and discussed. The formatting of the published and submitted manuscripts was modified prior to their incorporation into chapters to meet the standardized format of the thesis; however, their content represents an exact copy of the main findings as published or submitted. The thesis concludes with the last two chapters composed of a comprehensive discussion of the main findings, including advantages, limitations, novelty and future prospects (**Chapter 8)**, and a summary of the main points of evidence to the reader (**Chapter 9).** The bibliography can be found at the end and is followed by appendices that include the supplementary material of the published and submitted manuscripts along with the list of contributions to this project.

CHAPTER 2 LITERATURE REVIEW

In order to contextualize the thesis, the literature review will be presented in five sections. The first two sections, on electricity generation and energy storage systems, will introduce the reader to the context of the study and the importance of assessing energy systems. Section 3 on life cycle assessment, will explain the basics of this environmental evaluation method and emphasize the methodological limitations related to the evaluation of battery energy storage systems. The fourth section on external costs of energy highlights an important gap in the environmental assessments of power grids while section 5 elaborates on the common approaches to model and evaluate future grids including new technologies such as storage systems. Finally, this chapter is summed up with a clear statement of the problem.

2.1 Electricity generation

2.1.1 Overview

Energy is essential to the economic growth of societies (Ghosh, Tushar K. & Prelas, 2009). Over the last few decades, the rapid development of populations and the change in consumer habits increased energy use and electricity consumption (Guney & Tepe, 2017). A significant part of the total energy consumption is attributed to the manufacturing, transportation and construction sectors (Guney & Tepe, 2017). The world energy demand is estimated to double in the next couple of decades and triple by the end of the century (Lewis & Crabtree, 2005). Therefore, societies around the globe are faced with a real challenge to meet the projected energy needs (Larcher & Tarascon, 2015).

Traditionally, electricity was generated from non-renewable energy sources such as coal, oil and natural gas (NG). Long-term reliance on these sources is constrained by their uncertain available quantities and harmful emissions resulting from their processing, transformation, burning and use. With the increased climate change awareness, the detrimental environmental effects of fossil fuels burning (e.g. global warming, thinning of the ozone layer, acid rain, etc.) and their rapid depletion became the key drivers for power grids makeover (Sternberg & Bardow, 2015). Improving the conventional electricity production processes and upgrading technologies used for electricity

generation in existing infrastructures is no longer sufficient. To ensure the sustainability of the sector, it became mandatory to take preventive steps, pursue sustainable energy alternatives such as the use of energy-efficient methods for the production and consumption of electricity and rely on clean renewable energy sources (RES) (Guney, 2011; Larcher & Tarascon, 2015; Lewis & Crabtree, 2005).

The contribution of RES in electricity generation is rising worldwide. In 2012, RES constituted over 50% of the installed electricity generation capacity (Lins et al., 2013) with hydropower dominating the renewable generation capacity in several countries such as the United States and Brazil. Reliance on intermittent renewable energy like wind and solar power has remarkably increased over the last few years (Lins et al., 2013). It is therefore foreseen that wind and solar power will make up the majority of renewable electricity in the future (Sternberg & Bardow, 2015).

2.1.2 Renewable energy sources types, advantages, and disadvantages.

Renewable energy sources are naturally available power sources derived from natural phenomena of the environment (i.e. marine currents, wind movements, biological electron transfer systems and enzymatic reactions, *et cetera*) and include wind, hydro, and marine powers, in addition to geothermal, bio and solar energies (Ghosh, Tushar K. & Prelas, 2009; Mani & Gopala Rao).

The interest in RES increased due to their economic and environmental advantages. Renewable energy sources guarantee sustainable energy supply to governments and promote the development of remote regions. Investments in the development, implementation, operation, and maintenance of such technologies and infrastructures create employment and improve the population standard of living through direct (i.e. direct employment, development of remote regions, *et cetera*.) and indirect returns (i.e. cheaper energy cost, reduced pollution, *et cetera*.). In addition, renewable energy sources allow countries to reduce the impact of pollution on human health and the ecosystem (Sternberg & Bardow, 2015), fulfill international agreements relating to environmental protection and respect greenhouse gases (GHG) emission limits (Panwar, Kaushik, & Kothari, 2011; Zakhidov, 2008), therefore improving their fiscal budgets.

Despite multiple advantages, RES integration in power grids faces several limitations. For instance, hydropower sources can also cause damage to wildlife habitats, obstruct fish migration

(and affect reproduction), diminish the recreational benefits of rivers, and harm water quality (Ghosh, Tushar K & Prelas, 2011; Rand, 2018). Bio and geothermal energy sources can threaten the ecosystem (Ghosh, Tushar K & Prelas, 2011) and lead to augmented land use (Rinkesh), with sound, air, and water pollutions identified as potential negative consequences of geothermal based electricity generation (Lund, Freeston, & Boyd, 2011). Technological improvement and development of energy and cost-efficient energy production processes for both bio and geothermal energy sources are expected to reduce their limitations, and cost, allowing their broader adoption and inclusion in the electricity-mix. Wind and solar power are constantly growing and are expected to dominate the renewable electricity-mix in the near future (Steinke, Wolfrum, & Hoffmann, 2013) due to their decreasing cost, maturity, and footprint.

2.1.3 Electric grid challenges

The main objective of any power grid is to ensure a constant supply of electricity to meet consumer demand in terms of energy consumption. Therefore, electric grids and their operators are faced with multiple challenges including the optimization of energy production (i.e. day-to-day production) to meet hard to predict the fluctuation in energy demands (i.e. intra and inter-day fluctuations, seasonal fluctuations, *et cetera*).

Electric grids based on non-renewable energy sources (i.e. coal, oil, nuclear, natural gas) have been relatively easy to control over the years to achieve a quasi-optimal balance between supply and demand and reduce cost. However, the introduction of RES into the electricity-mix, to help mitigate environmental problems and reduce dependency on non-renewable energy sources, increases grid management complexity and poses new challenges. For instance, intermittent generation from these RES lead to both voltage and frequency fluctuations causing unstable operations of power systems (Ge et al., 2013; Ghosh, Tushar K & Prelas, 2011; Zhu et al., 2015) that could damage stability and quality of power supply (Guney & Tepe, 2017); *herein intermittency is defined as the unpredictable periods of energy generation that ensure continuity of energy supply*.

Absorbing power variability with the existing sources is easy for small RES penetration rates (~10-20%) (Beaudin, Zareipour, Schellenberglabe, & Rosehart, 2010). However, as RES penetration

rates increase with time, balancing supply and demand becomes difficult (Steinke et al., 2013) and new solutions must be implemented.

A potential solution to compensate for the RES intermittency and ensure network reliability include the use of large-scale Energy Storage Systems (ESS). ESS are considered among the most promising technologies to support the integration of renewable energy sources and to lower the emissions from electricity generation (Bradbury, Pratson, & Patiño-Echeverri, 2014; Bragard, Soltau, Thomas, & De Doncker, 2010; Denholm, Paul , Ela, Kirby, & Milligan, 2010; Krajačić et al., 2011; Raugei & Leccisi, 2016). ESS can stabilize fluctuations (Guney & Tepe, 2017), store power surplus, and supply power in peak demand periods reducing the reliance on non-renewable sources and demand curtailment (Chatzivasileiadi, Ampatzi, & Knight, 2013; Sternberg & Bardow, 2015). As a result of their advantages, ESS are expected to become a core component of future grids (Guney & Tepe, 2017) and a pillar of low carbon energy (Grünewald, Cockerill, Contestabile, & Pearson, 2011). Large-scale Energy Storage Systems are discussed in detail in the following **section 2.2** of this thesis.

2.2 Energy storage systems

2.2.1 Overview

As mentioned in **section 2.1** of this thesis, the intermittent nature of renewable energy sources (Shu & Jirutitijaroen, 2014) highlights the need for solutions that compensate for the intermittent nature of RES power generation and stabilize energy fluctuation (Narayanan et al., 2012; Prodromidis & Coutelieris, 2014). Large scale and cost-effective, Energy Storage Systems (ESS) possess several advantages motivating their use in the future power infrastructure (Narayanan et al., 2012; Zhao, Xu, Li, Gong, & Huang, 2012).

ESS store electrical energy following its conversion into other forms (Kiehne, 2003) and are usually classified as mechanical, electrochemical, electrical, thermochemical, chemical and thermal storage systems (IEC, 2011; Luo, Wang, Dooner, & Clarke, 2015) (Table 2.1). ESS can also be categorized according to their application type (i.e. portable or stationary) and duration of storage (short or long-term) (Ibrahim, Hussein, Ilinca, & Perron, 2008).

The choice of ESS is typically based on technical maturity, environmental impacts, capital energy cost, technical specifications, and most importantly on the desired application and scale (Sabihuddin, Kiprakis, & Mueller, 2014). Low life-cycle cost, fast response time, high efficiency and good scalability are the most important criteria for ESS implementation in electrical grids (Narayanan et al., 2012).

Energy storage systems are considered promising candidates to address some of the major issues of the future grid and enable smart grid concepts (Awad, Fuller, El-Fouly, & Salama, 2014; Beaudin et al., 2010; EPRI, 2010; Nykamp, Bosman, Molderink, Hurink, & Smit, 2013). They can provide several improvements in grid performance and seem to be a key component for adaptation to the varying consumer habits and activities (*Electricity Storage Technologies, impacts, and prospects*, 2015). In addition to enriching the renewable sector on large scale, energy storage systems improve grid reliability, provide ancillary services and relieve transmission congestions (Ge et al., 2013; IEA, 2018; Shu & Jirutitijaroen, 2014). They can store the surplus electricity produced and release this stored electricity when the resources are insufficient to satisfy energy demand (Chatzivasileiadi et al., 2013; IEA, 2018; Sternberg & Bardow, 2015). To ensure more economic operations, energy can also be stored in the ESS during low-price periods and discharged to the grid in high-price times (Shu & Jirutitijaroen, 2014). Therefore, the ESS can be operated such that they absorb power surges, limit load curtailment and save money (Awad et al., 2014; Bragard et al., 2010).

Despite their advantages, two main barriers to the development and extension of grid-scale storage systems emerge: **1-** grid-operators should be able to create the necessary infrastructure and space for the ESS deployment (TriplePundit), and **2-** ESS should comply with industry and regulatory requirements and constitute an effective mean for resolving grid interruptions and discontinuities (Bhatnagar & Loose, 2012).

Among the various large-scale storage systems (**Table 2.1**), mechanical pumped hydropower storage (PHS) systems come into prominence (Chatzivasileiadi et al., 2013) due to their facile operation (Esen, 2000; Esen & Ayhan, 1996; Esen, Durmuş, & Durmuş, 1998). However, PHS are limited in term of expansion due to the shortage of favorable geographic sites (Beaudin, Zareipour, Schellenberg, & Rosehart, 2014; Sternberg & Bardow, 2015). Global battery fleet, mainly lithium-

ion batteries, is rapidly growing and has doubled in the past three years (IEA, 2018). Battery energy storage systems (BESS) are moving into scientific focus and developments in their grid-scale applications have been gaining momentum due to their decreased costs and improved performance (Chatzivasileiadi et al., 2013; Díaz-González, Sumper, Gomis-Bellmunt, & Villafáfila-Robles, 2012; Ferreira, Garde, Fulli, Kling, & Lopes, 2013; Ibrahim, Hussein et al., 2008).

To support decision-makers, a comparative assessment of the proposed ESS with a focus on batteries is hence required (Sternberg & Bardow, 2015).

Table 2.1 Types of energy storage system available to date

Type of ESS	**Example**
Mechanical	Pumped hydroelectric storage, compressed air energy storage and flywheels
Electrochemical	Conventional rechargeable and flow batteries
Electrical	Capacitors, supercapacitors, and superconducting magnetic energy storage
Thermochemical	Solar fuels
Chemical	Hydrogen storage with fuel cells
Thermal	Sensible heat storage and latent heat storage

2.2.2 Electrochemical energy storage

Battery Energy Storage Systems (BESS) have various commercial energy storage products and hold the greatest diversity of research among all storage systems (Sabihuddin et al., 2014). BESS are expected to play a promising role in ensuring reliable operation of future smart grids (Divya & Østergaard, 2009; Dunn, Kamath, & Tarascon, 2011) due to their ability to reduce the cost of grid operation, and improve both power quality and system stability (Barelli, Desideri, & Ottaviano, 2015; Barnes & Levine, 2011; Besenhard, 2008; Bragard et al., 2010; Díaz-González et al., 2012; Divya & Østergaard, 2009; Dubarry et al., 2017; Dunn et al., 2011; Ge et al., 2013; Giraud & Salameh, 2001; Hadjipaschalis, Poullikkas, & Efthimiou, 2009; Hill, Such, Chen, Gonzalez, & Grady, 2012; Hittinger, Whitacre, & Apt, 2012; Leadbetter & Swan, 2012; Shayeghi, Shayanfar, & Jalili, 2009; Siano, 2014; Sternberg & Bardow, 2015; Zhou, Bhattacharya, Tran, Siew, & Khambadkone, 2011). In addition to meeting most of the requirements for grid-scale applications, batteries are more advantageous over the geographically constrained conventional ESS like PHS (Zhao et al., 2012).

Battery types vary according to the nature of the chemical reaction, structural features, and design (Daniel & Besenhard, 2011), and are classified as primary (non-rechargeable), secondary (rechargeable), reverse (primary battery with chemical segregation to limit self-discharge), or fuel cell. In power grids, secondary batteries are assembled, mounted into cabinet racks and installed in standard, or multiple, containers and deployed to make up a large easily maintainable battery plant (BatteryUniversity).

BESS remain relatively expensive for grid-related applications despite their price drop. The price of these systems decreased by ~ 85% over the past eight years (Goldie-Scot, 2019) and is expected to further decline due to technological advancement and intensive infrastructure investments (IEA, 2018). Additional factors delaying large-scale deployment of BESS include efficiency. The energy lost during the conversion and reconversion process significantly affects the cycle life of the batteries and their environmental profiles (Bhatnagar & Loose, 2012; Guney & Tepe, 2017). Lithium-ion batteries, characterized by their small discharge losses (<1% per month) and very high efficiency (>90%) are therefore recognized as the best candidates for application in power grids (BatteryUniversity; Bhatnagar & Loose, 2012).

2.2.3 Lithium-ion batteries

Lithium-ion (Li-ion) batteries are the most commonly used battery technology for energy storage since 1991 (BatteryUniversity). These batteries can be used in small (i.e. cell phones) or large scale applications (i.e. storing energy in power grids) (Barnes & Levine, 2011; Yoshio, Brodd, & Kozawa, 2009) and are growing in popularity for military and aerospace applications (Walker, 2015).

Li-ion batteries operate through the transfer of lithium ions between electrodes (Figure 2.1) (Yang, F., Wang, Zhao, Tsui, & Bae, 2018). Lithium ions move through an electrolyte (i.e. either liquid or solid) from the negative to the positive electrode during discharge, and back to the negative electrode during recharge. The high efficiency of Li-ion batteries is attributed to numerous factors including high energy density, low self-discharge and to the ion movements that leave the electrode structure intact, unlike other battery technologies (e.g. metal batteries) whose electrodes change by charging and discharging (Van Schalkwijk & Scrosati, 2002). Several active cathode materials are used for Li-based batteries (Van Schalkwijk & Scrosati, 2002) (Table 2.2); with Lithium Iron

Phosphate being the most frequent due to high stability, good electrochemical performance, low resistance, and safety (ACS, 2013). The major drawbacks of Lithium Iron Phosphate include low energy density causing its overall cost to rise. On the other hand, the most popular anodes used are graphites that are characterized by low cost and balanced performance. Their major drawbacks are the low theoretical capacity and cycling ability (Van Schalkwijk & Scrosati, 2002).

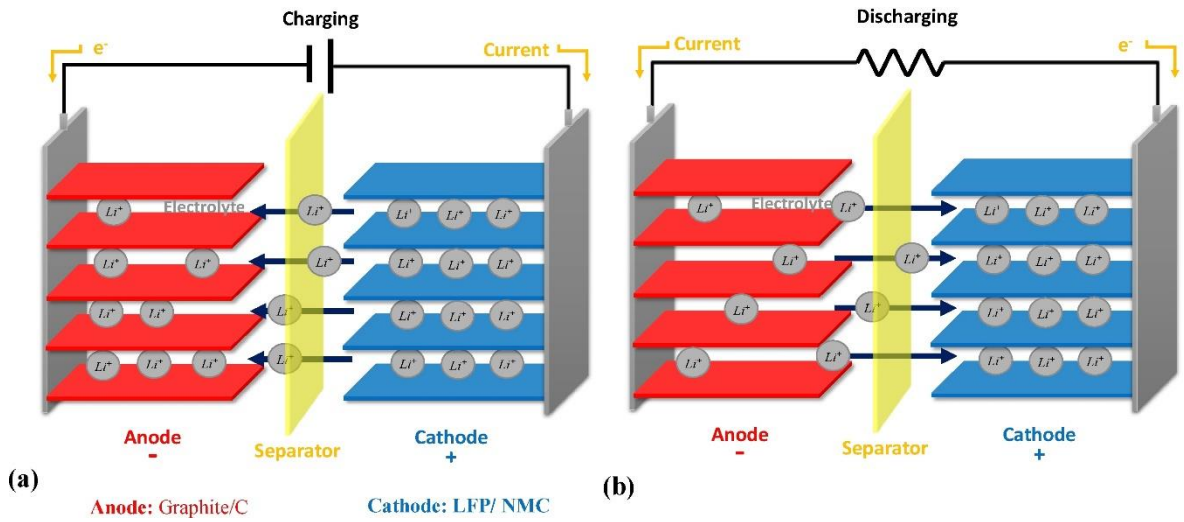

Figure 2.1 The operation of lithium-ion batteries when charging and discharging

Li-ion batteries are very flexible in their design and applicability regardless of their size. Their main characteristics include (Yoshio et al., 2009):

- ✓ *Reversibility:* They are known for their ability to dispatch and store energy in bulk
- ✓ *Speed:* They can dispatch and store power within a very short time (seconds to milliseconds)
- ✓ *Efficiency:* They can achieve an efficiency of 90-95% due to their ability to return almost all the energy they stored
- ✓ *Cost:* Their prices are falling while their size is sufficiently increased to be employed in various grid applications

Compared to other technologies (Table 2.3), lithium-ion batteries are cheaper and have improved energy density, greater cycle life and lower self-discharge rate (Bhatnagar & Loose, 2012). These

specifications, in addition to the maturity of this technology and safe operation, make it the most suitable BESS for grid-scale applications.

Table 2.2 Types of chemicals currently used to fabricate the cathodes of Li-ion batteries.

Abbreviation	**Name**	**Chemical formula**
LFP	Lithium Iron Phosphate	$LiFePO_4$
LMO	Lithium Manganese Oxide	$LiMn_2O_4$
LCO	Lithium Cobalt Oxide	$LiCoO_2$
LMNO	Lithium Nickel Manganese Spinel	$LiNi_{0.5}Mn_{1.5}O_4$
NCA	Lithium Nickel Cobalt Aluminum Oxide	$LiNiCoAlO_2$
NMC (NCM)	Lithium Nickel Cobalt Manganese Oxide	$LiNiCoMnO_2$
LTO	Lithium Titanate	$Li_4Ti_5O_{12}$

Table 2.3 Comparison of different battery technologies

		Criteria					
		Achieved upper limit power	**Specific energy (Wh/kg)**	**Specific power (W/kg)**	**Cycle life**	**Charge/discharge energy efficiency**	**Self-discharge**
Battery technology	**Lead acid**	Multiple tens of MW	35-50	75-300	500-1500	~80	2-5% per month
	Nickel cadmium	Tens of MW	75	150-300	2500	~70	5-20% per month
	Sodium sulfur	MW scale	150-240	90-230	2500	Up to 90	
	Lithium ion	Tens of kW	150-200	200-315	1000-10000	~95	~1% per month

	Nickel cadmium chloride	Tens/low hundreds of kW	125	130-160	2500+	~90	

Despite the advantages of these batteries, lithium is known for its toxicity and high reactivity. These batteries can therefore easily rupture, ignite, or explode when exposed to high temperatures, or direct sunlight (BatteryUniversity).

Aside from their chemical composition, these batteries are challenging at the environmental level. The mining activities of lithium and the production of energy needed for the manufacturing process are important sources of environmental impact in the life cycle of the batteries. Concerning their end-of-life, Li-ion batteries have very low potential recycling values compared to other technologies (Vandepaer, Cloutier, & Amor, 2017; Wang, X., Gaustad, Babbitt, Bailey, et al., 2014) and therefore have lower environmental benefits at this life cycle step. These batteries end up being incinerated or landfilled and unless it is legally enforced, their recycling will not occur due to poor or non-existent economic returns (Wang, X., Gaustad, Babbitt, Bailey, et al., 2014; Wang, X., Gaustad, Babbitt, & Richa, 2014; Zackrisson, Fransson, Hildenbrand, Lampic, & O'Dwyer, 2016).

At the use phase level, the environmental impacts are largely dictated by the sources charging the batteries and those substituted by its electricity production (Hawkins, Gausen, & Strømman, 2012; Hawkins, Singh, Majeau-Bettez, & Strømman, 2013; Majeau-Bettez, Hawkins, & Strømman, 2011; Notter et al., 2010). Compared to the manufacturing phase, the life cycle impacts from the battery operation are much greater (Hiremath, Derendorf, & Vogt, 2015). It is, therefore, crucial to accurately model and assess the lithium-ion batteries use to better understand the sources of impacts and propose convenient solutions.

2.3 Life cycle assessment

2.3.1 Background

It became well known that a large segment of the environmental impact of a given product or service is not related only to its use; instead, its production, transportation, and disposal also have considerable contributions (Guinee et al., 2011). Environmental managers and policymakers require therefore a holistic approach to evaluate their systems (Curran, 2013).

Life cycle assessment (LCA) is a holistic environmental evaluation method that studies products (i.e. goods or services) from "cradle to grave". It examines their potential environmental impacts, throughout all their life cycle phases including raw material extraction, manufacturing, use phase, and end-of-life processes (ISO, 2006a). The LCA milestones have been harmonized on a global level within a series of international standards by the International Organization for Standardization (ISO). ISO standards 14040-14044 (ISO, 2006a, 2006b) describe its framework, detail its principles and specify four interrelated steps for any LCA. Figure 2.2 depicts the LCA's methodological framework and the description of the steps follows (ISO, 2006a).

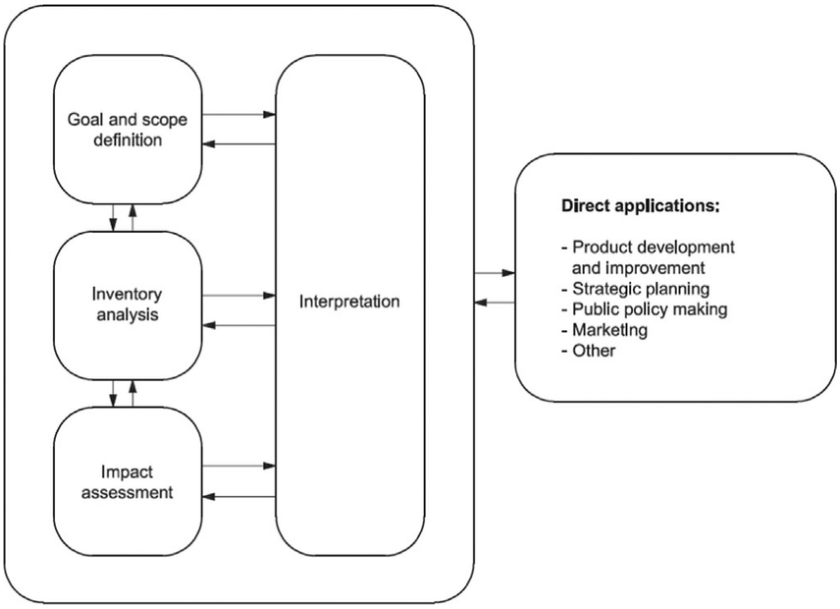

Figure 2.2 LCA Framework as defined by ISO 14040

- **Goal and Scope**: In this step, the study's objectives are defined and the system's boundaries are set. Numerous parameters are to be specified at this step too including the

product's primary and secondary functions and the functional unit which is a quantified representation of a product system's performance. If the study performed is a comparison between two alternatives, it must be stated here. In this step also, the time frame and the depth of the study's details are specified

- **Inventory Analysis:** Each life cycle process's inputs and outputs of the product or service are compiled at this step, in addition to the quantification of the emissions and resources. A description of every unit process is also provided. The objective of the inventory analysis is to list all the substances that are emitted into/or extracted from the environment during the life cycle of the product or service.
- **Life cycle impact assessment:** Three elements can be included in this step of the LCA and they are the classification, the characterization, and the weighting. The impact categories are selected, and the emissions are classified under the corresponding classes. Substances listed in the inventory analysis are converted into environmental impacts corresponding to several impact categories based on "cause and effect" chains (impact assessment models). The computation can be performed at the midpoint level, using incomplete cause and effect chains, or at the endpoint level, if performed at the end of the chain.
- **Interpretation:** By interpreting the results of the two previous phases, answers are provided to the objectives stated in step one. Analysis of uncertainty and sensitivity can be performed during this phase.

According to ISO 14040 (ISO, 2006a) and the Environmental Protection Agency (EPA) guide (Jensen et al., 1997), LCA can have various areas of application including product development, public policymaking, process optimization, marketing, strategic planning, decision making, etc. A common goal behind many LCAs is the identification of the areas of potential amelioration in a specific field or sector (ISO, 2006b). The evaluation of the system throughout its entire life cycle allows the determination of the most emitting procedures and tracking of the environmental impact displacement between various steps. LCA is also an essential screening tool. It can prevent burden environmental impacts shifting between different phases of the life-cycle (Finnveden, G. et al., 2009) by pointing to the hotspots within the complex value chains (Hellweg, S. & Mila i Canals, 2014).

Most importantly LCA is a robust tool used by many governmental agencies, firms, and policymakers to support their decision-making and environmental optimization procedures (Curran, 2013; Finnveden, G. et al., 2009). It can help minimize pollution's magnitude and conserve both ecological systems and conventional resources. In addition, it allows the comparison between alternatives, contributes to the development and utilization of cleaner technologies and allows the maximization of the material and waste recycling (ISO, 2006b).

Life cycle assessment models evolved towards the identification of environmental consequences of changes in systems and witnessed a remarkable increase in their sophistication and topics of concern (Dones, Menard, & Gantner, 1998; Frees & Weidema, 1998; Guinee et al., 2011; Weidema, Bo P., Frees, & Nielsen, 1999; Wenzel, 1998). This evolution led to the distinction between two main types of LCA, the attributional and the consequential (Curran, Mann, & Norris, 2005).

2.3.2 Types of LCA

- **Attributional LCA**

The attributional LCA (A-LCA) is the type of assessment, which describes the system as it is actually at a certain time (Finnveden, 2008). It is the conventional environmental evaluation method and it accounts for the physical relationships of a system's impacts (Weidema, Bo P. et al.) by assigning the elementary flows and the potential environmental impacts to the product system studied while considering its history (ISO, 2006a). This assessment includes all the processes which have a significant contribution to the product of concern and to its function (Rebitzer, G. et al., 2004). In the modeling of the system's life cycle regional or average data, are usually used (Tillman, 2000).

In several fields of study, A-LCA is constrained by its lack of insights on the product's economic characteristics (Guinée, Jeroen B., 2002) and the use of average data which can mask the details (Weidema, Bo P. et al., 1999). These practices can limit its application for decision-making purposes where the inclusion of information about the resulting consequences is necessary (Ekvall,

Tomas & Tillman, 1997). Therefore, the use of C-LCA becomes more convenient (Yang, Y., 2016).

- **Consequential LCA**

The consequential life cycle assessment (C-LCA) is used to study the environmental consequences resulting from possible changes between alternative systems of the product (ISO, 2006b). More precisely, it accounts for the consequences resulting from a given choice and for the short and/or long-term environmental impacts of these decisions (Finnveden, 2008; Sandén & Karlström, 2007). This type of assessment is also known as Change-Oriented LCA (Sandén & Karlström, 2007).

The C-LCA makes use of economic data in order to measure the physical flows attributed to the processes indirectly affected (Weidema, B. P., 2003). The processes to be included in this type of assessment are those anticipated to be affected by the decisions made (Rebitzer, G. et al., 2004). C-LCA accounts therefore for both direct and indirect consequences of the systems. Whenever the consequences represent proportionally the relations between the life cycle phases and the environmental impacts, they are known as direct consequences (Sandén & Karlström, 2007) and they are usually assessed using the conventional LCA method (Ekvall, Tomas & Weidema, 2004). Indirect consequences include in addition to the direct consequences, the effects of both the physical and the economic flows (Sandén & Karlström, 2007). To evaluate indirect consequences, C-LCA is usually coupled to other models (Bouman, Heijungs, Van der Voet, van den Bergh, & Huppes, 2000; Ekvall, T., 2002; Ekvall, Tomas & Andrae, 2005).

At the application level, the consequential LCA has been proven suitable for decision-making (Finnveden & Ekvall, 1998; Finnveden, Göran et al., 2009; Menten, Tchung-Ming, Lorne, & Bouvart, 2015; Weidema, B P, 2015; Weidema, Bo Pedersen, Ekvall, & Heijungs, 2009). It helps evaluate the decision's environmental consequences, which are dependent on many factors including the economic, technological and environmental mechanisms (Finnveden, G. et al., 2009). The C-LCA is indispensable in the interpretation of the results of a given change occurring in the processing of a product, especially when the consequences do not vary linearly with the magnitude of that change, such as the operation of electric grids (Rebitzer, G. et al., 2004).

The application of C-LCA can be limited mainly by 1) the uncertainty of the estimated consequences, since the assessments can only provide an insight on the expected environmental impacts (Sandén & Karlström, 2007), and 2) the lack of time information since the scope of the C-LCA, similarly to that of the A-LCA, do not include any notion of time (ISO, 2006b).

A-LCA and C-LCA can be both retrospective and prospective; however, the inclusion of the time factor in these methodologies is still considered tight (Guinee et al., 2011). Severe errors can result from the steady-state assumption made in the traditional LCAs (Reap, Roman, Duncan, & Bras, 2008), the dynamic LCA was therefore developed.

- **Dynamic LCA**

The conventional LCA framework, lacking dynamic representations is indifferent to the time dimension related to the environmental impact assessment (de Haes et al., 1999; Hellweg, Stefanie, Hofstetter, & Hungerbuhler, 2003; Reap et al., 2008). Since, the accuracy of the LCA performed is noticeably influenced by the temporal patterns of the different life cycle stages, such as the production, the use, and the disposal, the resolution of time-related problems becomes crucial. The inclusion of the time factor will certainly help to develop the existing LCA methodologies and would contribute to the improvement of their environmental relevance (Collinge et al., 2012; Reap et al., 2008). The adoption of a dynamic assessment technique is, therefore, essential. Levasseur et *al.* (Levasseur, A., Lesage, Margni, Deschenes, & Samson, 2010) were among the first to propose a dynamic LCA (D-LCA) method to address the temporal assessment inconsistencies. They emphasized the need to include the temporal aspects at both inventory and impact assessment levels. The D-LCA can contribute to a better understanding from the side of the decision-makers, by providing clearer insights at the different life cycle steps on the locations and timings of the potential impacts, their frequency and intensity (Fouquet et al., 2015; Lebailly, Levasseur, Samson, & Deschênes, 2014; Levasseur, Annie, Lesage, Margni, Brandão, & Samson, 2012).

Despite improving the representativeness of the studied systems by the D-LCA, the time factor is still considered a problem in LCA (Beloin-Saint-Pierre, Levasseur, Pinsonnault, Margni, & Blanc, 2013; Reap et al., 2008). Collecting temporal information on the modelled systems is a time-consuming and challenging task, which limits the application of D-LCA (Pinsonnault, Lesage, Levasseur, & Samson, 2014).

To evaluate time-variant systems such as electricity generation, recent researches have addressed the need for the integration of other models with LCA in addition to temporal data, to better represent the temporal variability of the systems (Guinee et al., 2011; Vazquez-Rowe, Marvuglia, Rege, & Benetto, 2014).

2.3.3 LCA of electricity generation

Analyzing the environmental life cycle impacts of the electricity generation processes is crucial to limit their adverse impacts on the environment (Turconi et al., 2013; Varun, Bhat, & Prakash, 2009). The Life Cycle Assessment method offers a conceptual framework for a precise and comprehensive comparison of electricity supply options since the evaluation scope accounts for all direct and indirect emissions from the exploration, extraction, fuel processing, transportation, energy conversion, waste management, and storage steps (Dandres, T., R. F. Moghaddam, K. K. Nguyen, Y. Lemieux, M. Cheriet, and R. Samson, 2014; Voss, 2001). The infrastructure, fuel provision, and plant operation have been proven among the most difficult life cycle steps to assess (Turconi et al., 2013). While renewable energy sources are non-emitting during their operation, accounting for their entire life cycle emphasizes the environmental impacts from the procurement of the material, their manufacturing, and transportation (Curran et al., 2005; Khan, F. I., Hawboldt, & Iqbal, 2005).

LCAs of electricity generation differ according to several factors including the local conditions, the technical characteristics, the research questions, the data set selection and the methodological choices adopted (Soimakallio, Kiviluoma, & Saikku, 2011). The adequate determination of the system's boundaries (i.e. what is included and/or excluded from the assessment) is also an important step in the evaluation of electricity generation systems. In (Amor, Billette de Villemeur, Pellat, & Pineau, 2014), the authors included imports and exports of electricity produced, which were proven to have an effect on the local generation and altered the amount of emitted GHG consequently (Amor, Pineau, Gaudreault, & Samson, 2011).

When evaluating the electricity generation, a common practice is the determination of the marginal source of electricity. This source is defined as the power plant capable of adapting its power generation to the changes in the market and consumers' needs. Accordingly, the sum of all the

electricity generated by these marginal sources would constitute the marginal electricity (Dandres, T., R. F. Moghaddam, K. K. Nguyen, Y. Lemieux, M. Cheriet, and R. Samson, 2014).

The environmental impacts from the different electricity generation technologies can be estimated in different methods based on marginal emissions, average emissions or a combination of both (Amor, Billette de Villemeur, et al., 2014). The attributional approach, using average data is useful in the assessment of the average life cycle GHG emissions of the entire electricity generation process (e.g. (Amor, Gaudreault, Pineau, & Samson, 2014; Amor, Lesage, Pineau, & Samson, 2010; Maurice et al., 2014; Rehl, Lansche, & Müller, 2012; Soimakallio et al., 2011)). However, since annual averages mask the hourly variations and the difference between shorter time and annual periods can be highly relevant, applying the marginal approach by means of a consequential LCA improves the accuracy of the assessments by better-representing changes in the grid (Amor, Billette de Villemeur, et al., 2014; Amor et al., 2010; Dandres, T. et al., 2017; Wang, C., Wang, Miller, & Lin, 2016).

Despite the improvements made, the assessment of environmental impacts from electricity generation is a complex task due to 5 main factors (Curran et al., 2005):

1. The power grids' broad geographic scope and electricity markets
2. The dynamics of operation to respond to the varying demands
3. The variation of generation in terms of inputs, fuel types, and sizes
4. The variability of local energy targets and emission limits
5. The difference in electricity generation technologies, their life cycles and their evolution

2.3.4 LCA of BESS

The life cycle assessment of various energy storage systems was performed to better understand the environmental impacts of these technologies (Ari & Baghzouz, 2011; Butler, Iannucci, & Eyer, 2003; Denholm, Paul & Kulcinski, 2004; Faria et al., 2013; Hiremath et al., 2015; Jing, Bai, Wang, & Liu, 2012; Longo, Antonucci, Cellura, & Ferraro, 2014; Ma, Yang, & Lu, 2014; Römer, Reichhart, Kranz, & Picot, 2012; Rydh, 1999; Sullivan & Gaines, 2012; Tsai-Hsiang, Ying, Ting-Yen, & Wei-tzer, 2013; Van den Bossche, Vergels, Van Mierlo, Matheys, & Van Autenboer, 2006; Yan et al., 2011; Yu et al., 2012). Numerous studies focused on battery energy storage systems for

automotive applications (Hawkins et al., 2013; Majeau-Bettez et al., 2011; Matheys et al., 2007; Notter et al., 2010; U.S.EPA, 2013) and emphasized the manufacturing step assuming it is the most impactful (Guney & Tepe, 2017; Sternberg & Bardow, 2015; Technology). It became more important to fill the gap in the literature and perform a detailed study of the entire life cycle of the batteries when recent works proved that the environmental impacts resulting from the ESS operation are far more important than its manufacturing (Hiremath et al., 2015; Sullivan & Gaines, 2012).

Battery energy storage systems for utility-scale applications were assessed (Bila, Opathella, & Venkatesh, 2016; Consiglio et al., 2013; Denholm, Paul & Kulcinski, 2004; Frischknecht et al., 2018; IRENA, 2015a, 2015b; Khasawneh, Mondal, Illindala, Schenkman, & Borneo, 2015; Koller, Borsche, Ulbig, & Andersson, 2015; Longo et al., 2014; Lu, Xu, Pan, & Song, 2014; Marini, Latify, Ghazizadeh, & Salemnia, 2015; Reihani, Sepasi, Roose, & Matsuura, 2016; Rydh, 1999; Rydh & Sandén, 2005a, 2005b; Shen, Dusmez, & Khaligh, 2014; Subburaj, Pushpakaran, & Bayne, 2015; U.S.DoE; Vandepaer, Cloutier, Bauer, & Amor, 2018). However, most of the studies focused on modelling the manufacturing step from generic databases with only a few actual field studies of a grid-scale BESS operating under real grid constraints (Bila et al., 2016; Consiglio et al., 2013; IRENA, 2015a, 2015b; Koller et al., 2015). Since the various grid technologies dictate the electricity charging the storage system and consequently affect the avoided impacts from its operation (Oliveira et al., 2015) enhancing the use phase assessment of these systems became crucial.

Among a large number of BESS projects already in place (Subburaj et al., 2015; U.S.DoE), the assessment of Li-Ion batteries proved that this technology is more promising for grid-scale application than its competitors at the various life cycle stages since it has the lowest impacts throughout their entire life cycle (Hiremath et al., 2015). To support investors and grid-operators in making informed decisions, the potential environmental impacts from the operation of Li-ion batteries in the power grid needs to be accurately assessed while accounting for the grid constraints and the temporal variability of the systems.

2.4 External costs of energy

2.4.1 Externalities of electricity generation

An external cost, or externality, can be defined as the cost of the damage which is not included in the purchase price of a technology/ commodity (Pearce & Barbier, 2000). In the case of the energy sector, the external costs result from the damages during fossil fuel extraction, transportation, and energy use (Machol, B. & Rizk, S., 2013; Patrizio, Leduc, Chinese, & Kraxner, 2017) and they are usually not considered in the full cost (Bickel & Friedrich, 2004; Machol, B. & Rizk, S., 2013; Turtós Carbonell, Meneses Ruiz, Sánchez Gácita, Rivero Oliva, & Díaz Rivero, 2007). To ensure the sustainability of the sector and reflect the true cost of electricity, it is important to account for the environmental impacts at various levels (human health, crops, building materials, ecosystems, climate, etc.) (Bickel & Friedrich, 2004; Sakulniyomporn, Kubaha, & Chullabodhi, 2011; Treyer, Bauer, & Simons, 2014; Voss, 2001).

One of the most common approaches to account for these damages is to internalize their cost into the price of electricity (Voss, 2001). To be able to internalize the externalities, the environmental damages resulting from the energy conversion processes need to be quantified and monetized first. Using monetary values facilitates the task of accounting for externalities, makes the concept more comprehensible by the public and allows their incorporation in the energy-related decisions (Patrizio et al., 2017).

To internalize externalities, two main approaches are used 1) Eco-taxing, which consists of taxing damaging fuels and technologies based on the external costs caused, and 2) Subsiding cleaner technologies (ExternE; García-Gusano, Istrate, & Iribarren, 2018).

Accounting for externalities helps policymakers achieve their sustainability goals, make informed decisions and enforce pollutant fees (Machol, B. & Rizk, S., 2013; Pearce & Barbier, 2000; Streimikiene, Roos, & Rekis, 2009; Zhang, Weili, Yumei, & Yingxu, 2007). Internalizing these costs also allows the promotion of new and clean technologies by making their prices competitive to that of fossil fuels (Sakulniyomporn et al., 2011; Streimikiene et al., 2009; Zhang et al., 2007), helps achieving the full picture of the consumption of resources (Voss, 2001) and adjusts the energy structure [23]. In addition, it can result in large quantifiable economic benefits (U.S.EPA;

U.S.EPA; U.S.EPA, 2015; Weldu, Yemane W & Assefa, 2016), help mitigate the adverse impact of electricity generation and ensure the benefit of the society (García-Gusano, Istrate, et al., 2018; Sakulniyomporn et al., 2011).

2.4.2 Externalities in LCA

To integrate the sustainability concepts in the energy policies and design of future energy systems, it has been recommended to use externalities based on life cycle emissions (García-Gusano, Istrate, et al., 2018). LCA is, therefore, the starting point for the evaluation of energy systems and is applied to quantify the damage of electricity generation to climate change, ecosystem quality and human health (Voss, 2001). In order to overcome the limitations of the difference between the metrics used in LCA and other decision-making tools, have a common ground for the comparison of the different technologies and avoid the subjective weighting in LCA, these environmental impacts must be transformed to monetary units and be explicitly included in the final costs (Algunaibet, Pozo, Galán-Martín, & Guillén-Gosálbez, 2019; Dong et al., 2018; Pizzol, Weidema, Brandão, & Osset, 2015; Streimikiene et al., 2009). Expressing the impacts in monetary values is important since it increases the awareness of the indirect costs of pollution and makes the communication of the LCA results easier (Algunaibet et al., 2019). Monetizing the impacts facilitates the optimization of energy systems in terms of environmental impacts and costs of operation simultaneously (Pizzol et al., 2015). However, the internalization of externalities is constrained by the ability to assign costs to the ecosystem and human health damages (Turtós Carbonell et al., 2007). In the scientific community, there is a lack of consensus on the most appropriate monetization method to weigh the environmental impacts of LCA (Nguyen, Laratte, Guillaume, & Hua, 2016). Despite the limitations associated with the external costs and which can be related to the technological options, regional differences, and monetization approaches, some insights can still be derived from this practice of including externalities.

2.5 Future grid assessment

2.5.1 Prospective LCA

Prospective LCA has been developed in response to traditional retrospective life cycle analysis. Potential changes or decisions that could affect the system are taken into account during the prospective analysis to better predict future scenarios. The prospective analysis of the life cycle does not predict the future but rather explores future technological systems and their environmental profiles through the evaluation of a range of scenarios (Cucurachi, van der Giesen, & Guinée, 2018). Inclusion of future, or potential, scenarios allows decision and policymakers to better understand the projected future of emerging technologies (Hung, Ellingsen, & Majeau-Bettez, 2018; Wender et al., 2014), their large-scale implementation (as in (Hertwich et al., 2015; Navas-Anguita, García-Gusano, & Iribarren, 2018)) and the effectiveness of the energy plans (e.g. (García-Gusano, Iribarren, & Garraín, 2017; Norwood, Goop, & Odenberger, 2017)) and visualize the impact of their present decisions and design choices on the predicted environmental performance of a technology. Equipped with such data, decision and policymakers can diminish costs, prevent environmental burdens, and/or regrettable investments (and/or technology substitutions), and predict variations in environmental regulations (Cucurachi et al., 2018).

In spite of the merits of this approach, the prospective analysis has three major limitations (Navas-Anguita et al., 2018), including uncertainty, scarce data and the need to make assumptions regarding future contexts and social implications; Table 2.4.

Table 2.4 Main limitations of prospective LCA

Limitation	**Example**
Uncertainty	The future product/system might have different functionality; the scenarios might overlook important flows in the future system, price trajectories will differ, and impact assessment methods might not cover all pertinent impact categories
Data	Data on future systems and products are scarce

Assumptions	Need to make some assumptions about relevant social implications, future contexts of use/application, and future emission factors

To evaluate future systems, several LCA practitioners carried out prospective consequential LCA studies (e.g. (Dandres, T., Gaudreault, Tirado-Seco, & Samson, 2011, 2012; Jones, Gilbert, Raugei, Mander, & Leccisi, 2017)). The aim of these studies was to describe the effects of changes within the life cycle of the systems and to account for the environmental consequences of decisions. This approach has been proven relevant particularly for the assessment of electricity mixes. However, due to the complexity of the power sector, LCA is usually combined with other methods to analyze the operation of future grids, among other environmental scenario analyses (e.g. (Hertwich et al., 2015; Martín-Gamboa et al., 2019)) and energy system models (e.g. (García-Gusano et al., 2016; Vandepaer et al., 2018)).

2.5.2 Environmental scenario analysis and LCA

Environmental Scenario Analysis (ESA) is defined as the process of elaborating different scenarios, comparing, and assessing their outcomes (Alcamo, 2008a). In other words, it is a tool used to anticipate prospective developments of society and nature and evaluate the strategies required for these developments (Alcamo, 2008a). ESA facilitates the interpretation of environmental problems in a large scope covering a wide range of sustainability-related issues (Alcamo, 2008a, 2008b) by representing the interactions between society and the various environmental compartments. In contrast to other environmental evaluation methods, ESA is flexible, comprehensive, and cheap (Alcamo, 2008a).

ESA is also often used to establish policy-relevant studies, enhance the evaluation of both the technical and legal implications of environmental regulations and support strategic planning (Alcamo, 2008b). It has been used to study different types and scales of complications like global sustainability or specific environmental issues like changes in emissions, air quality, or land cover in a specific district or region (Alcamo, 2008a).

ESA can be divided into two types of analysis: Inquiry-driven and Strategy-driven scenario analysis. *Inquiry-Driven scenario analysis* aims to increase scientific knowledge and provide input

to stakeholders. It produces future scenarios using computer models and then assesses their environmental profiles. *Strategy-Driven scenario analysis* is mainly used to draft and evaluate strategies in order to improve environmental quality. It is mainly used by policymakers and the business community for corporate planning (Duinker & Greig, 2007).

The application of ESA offers numerous benefits to environmental scientists and policymakers (Alcamo, 2008a). ESA helps environmental scientists raise awareness about new or increasing environmental problems, provides an interdisciplinary basis for analyzing complex environmental problems and foreseeing solutions to these problems and organizes and communicates numerous information about the evolution of an environmental problem. As for policymakers, ESA provides pictures for future alternative states of the environment to point out the effectiveness of policies in avoiding environmental impacts. ESA also identifies the strength of environmental policies under different future conditions and provides an opportunity for stakeholders to interfere with the development of public policies.

Despite its advantages, the application of ESA is constrained by several limitations. The results of ESA are not always comprehensible to non-scientific audiences which limits the communication of the findings (Duinker & Greig, 2007). Furthermore, ESA does not always reflect the needs of stakeholders and policymakers (Alcamo, 2008a). Therefore, the need to combine ESA with a robust decision-making tool, such as LCA, arises.

The importance of linking two environmental evaluation methods such as LCA and ESA resides in their complementarity. ESA relies on models, scientific literature and documentation to generate scenarios and provide numerical information for environmental studies (Alcamo, 2008b). On the other hand, LCA is a robust scientific method used to evaluate the environmental footprint of systems and products from cradle-to-grave (Guinée, Jeroen B, 2002). It also allows an unbiased and consistent comparison of systems fulfilling the same need (such as the production of 1kWh of electricity) (Treyer & Bauer, 2016). The LCA can help in overcoming some of the ESA's limitations since it facilitates the interpretation of the environmental evaluation results and helps communicate them to non-specialists (Alcamo, 2008b; Jolliet, Saade-Sbeih, Shaked, Jolliet, & Crettaz, 2015). Hence, linking LCA and ESA is highly relevant to the investigation of the electricity sector and its corresponding goals over the short-term. The combination of LCA and

ESA has already been performed in previous works (e.g. (Bauer, Hofer, Althaus, Del Duce, & Simons, 2015; Tevis, Schuster, Evans, Himmler, & Gheewala, 2019; Tsoy, Prado, Wypkema, Quist, & Mourad, 2019)) and some of them focused on electricity generation (e.g. (Treyer & Bauer, 2016)). However, most of these studies based the scenario developments on literature and assumptions. The combination of LCA and ESA is not yet addressed in the context of short-term operation optimization in accordance with energy targets. There is, therefore, a need for a new method that goes beyond this limitation, facilitates near-real assessment conditions and improves the accuracy of the environmental assessment in the short-term (i.e. 1 to 5 years) (Tevis et al., 2019).

2.5.3 Energy system modelling and LCA

Energy systems are defined as the entire supply chain of energy from the extraction of resources to its final consumption in services (Team, 2012). It is crucial to model energy systems using appropriate tools in order to support decision-makers during the planning phase (Nakata, 2004; Nerini et al., 2018; Spittler, Gladkykh, Diemer, & Davidsdottir, 2019; UN, 2016).

Energy system models (ESMs) are mathematical models developed to represent different energy-related problems (Kondili, 2010). They are used to identify and solve energy issues, or to aid in the quantification of scenario details (e.g. technological influence) (Hall & Buckley, 2016; Kondili, 2010). ESMs are used in an exploratory manner to project the future energy demand and supply of a region/country or to motivate technology choices and policies while considering factors such as energy prices and economic activities (Spittler et al., 2019). Therefore, they facilitate the development of optimized operation scenarios while accounting for future technologies, a wide range of services, energy targets and market dynamics (Herbst, Toro, Reitze, & Jochem, 2012).

Energy system modelling tools have been constantly changing depending on the subject matter (i.e. context) (Spittler et al., 2019) with models typically classified into one of the two approaches *viz.* bottom-up or top-down (Herbst et al., 2012).

Bottom-up models focus on the technological complexity of the energy system and aim to create a set of useful scenarios for the long-term future evaluation of key parameters such as electricity, emissions, and costs. They generally require a large amount of data due to the level of details

considered during the analysis (Bhattacharyya & Timilsina, 2010; García-Gusano, Garraín, & Dufour, 2017; Hourcade, Jaccard, Bataille, & Ghersi, 2006; Nakata, 2004; Pfenninger, Hawkes, & Keirstead, 2014), they only consider GHG emissions and ignore the development of the systems between short and long- terms (E3MLab, 2016; Hourcade et al., 2006; Loulou, R.; , Goldstein, & Noble, 2004; Loulou, Richard, Remme, Kanudia, Lehtila, & Goldstein, 2005).

Top-down models focus on the interaction between the various sectors of the economy and often overlook energy technologies (Spittler et al., 2019). These models enable tracking of the emission targets as they consider GHG emissions and other pollutants as part of the economic sector (Spittler et al., 2019).

ESMs used by policymakers do not explicitly tackle sustainability-related issues and provide a limited understanding of the energy systems' role in the sustainability pathways (García-Gusano, Garraín, et al., 2017; Spittler et al., 2019). There is, therefore, a need to go beyond climate change, address additional environmental impacts and look at damages to human health, land use and water (Dai et al., 2018; IPCC, 2012). Hybrid models are therefore used to address the limitations of ESM models and answer relevant energy-related questions (García-Gusano, Garraín, et al., 2017; Spittler et al., 2019).

Since the LCA is one of the most established methods to evaluate the potential environmental impacts of systems, coupling ESM with LCA is recommended as a solution to develop a more comprehensive environmental evaluation of energy systems and discuss the alternative options to improve it (Bouman et al., 2000; García-Gusano, Garraín, et al., 2017; Menten et al., 2015).

Combining LCA and ESM methods improves the understanding of the economics of the system, better represents the market mechanisms and allows the practitioners to deal with environmental issues simultaneously (Eriksson, Finnveden, Ekvall, & Björklund, 2007; Mathiesen, Münster, & Fruergaard, 2009; Pehnt, Oeser, & Swider, 2008; Röder, 2001). This combination offers a flexible way to address challenges in energy systems (Pieragostini, Mussati, & Aguirre, 2012).

LCA practitioners frequently relied on ESM to explore future scenarios and evaluate the potential environmental impacts of electricity generation (Astudillo, Vaillancourt, Pineau, & Amor, 2017; García-Gusano, Istrate, et al., 2018; Krook-Riekkola, Berg, Ahlgren, & Söderholm, 2013). Such practice has been applied to study the systems' operation in various geographical locations using

different energy models (Bouman et al., 2000; Choi, Friley, & Alfstad, 2012; Dandres, T. et al., 2011, 2012; García-Gusano, Garraín, et al., 2017; García-Gusano et al., 2016; Krook-Riekkola et al., 2013; Menten et al., 2015; Pietrapertosa, Cosmi, Macchiato, Salvia, & Cuomo, 2009; Röder, 2001; Treyer & Bauer, 2016).

In spite of their numerous advantages, ESM are time-consuming to build and complex to run. The comprehensive analysis of policies and decisions becomes difficult to reach because of the fragmentation of these models and the large amount of data required (Pang, Mörtberg, & Brown, 2014). In addition to their temporal scope designed for mid-to-long term assessments, and their narrow scope of environmental evaluation focusing on GHG emissions, there is a need for further improvements. A new simple model is therefore needed to support policymakers (Lacirignola, Meany, Padey, & Blanc, 2014; Padey, Blanc, Le Boulch, & Xiusheng, 2012; Padey et al., 2013; Raugei & Leccisi, 2016). This model should: 1) be, applicable for short-term evaluations, 2) optimize the and including the optimization of the sector, 3) is therefore needed to support policymakers. It should take be capable of taking into account the economics of operation and 4) provide a robust environmental evaluation of the system under study (Lacirignola et al., 2014; Padey et al., 2012; Padey et al., 2013; Raugei & Leccisi, 2016).

2.6 Problem statement

Numerous LCA studies have been performed to evaluate the environmental impacts of electricity generation. However, attempts to assess the existing systems, their operational technologies and also future energy alternatives haven’t been very successful. Policymakers still consider LCA somewhat inconclusive due to several limitations, among which three were considered important to address:

1- The lack of system dynamics in the use phase assessment of new technologies deployed in power grids, such as energy storage systems

2- The limited consideration of the external cost of electricity and its impact on the operation of energy storage technologies

3- The need for a framework for the environmental assessment of power grids in the short-term

Accounting for the temporally variable operation of new technologies is essential to steer and evaluate policies regarding the environmental impacts of future grids. For instance, prior to shifting to a renewable-based electric grid, there is a pressing recommendation to remarkably enhance the grid's ability to store energy. Assessing various energy storage systems and comparing their potential environmental impacts is therefore crucial. There is a need for a new LCA method to evaluate the potential environmental impacts from the operation energy storage systems in power grids while considering their temporal aspects.

Furthermore, the external cost of electricity generation including the cost of damage to human health and ecosystem quality must be considered in the optimization of electric grid operation since these costs affect the operation of the various technologies and consequently their environmental profiles. To better evaluate the role of new energy storage systems in power grids, it is important to evaluate the consequence of internalizing these costs on the avoided environmental impacts from their operation and on their potential cost reductions.

Finally, the structure of power grids is changing to include new renewable energy sources and energy storage systems. It is, therefore, crucial to assess these grids in the short-term, evaluate the decisions made and validate if they align with the energy targets and emissions limits. While numerous methods are available for long-term assessments, the evaluation of power grids in the short-term, while optimizing the grid operation and accounting for new technologies, is still lacking.

To address these challenges, improve confidence in the LCA results, and enhance the decision-making process, some methodological improvements are needed. A new life cycle assessment method to assess the environmental impacts of energy storage systems in power grids is required.

CHAPTER 3 RESEARCH OBJECTIVES AND METHODOLOGY

3.1 Research question

The methodology developed in this thesis answers the following question: "How to assess the potential environmental impacts of energy storage systems in power grids?"

3.2 Hypothesis

The optimized-consequential life cycle assessment, combining temporally differentiated inventory data and optimization algorithm within the LCA approach, is an adequate method to assess the environmental impacts of energy storage systems in power grids.

3.3 Objectives

The main objective of this research is to: "*Develop a new life cycle assessment method to evaluate and compare the potential environmental impacts of energy storage systems in power grids*."

To achieve the main objective, several sub-objectives were devised as follow:

1. Incorporate the dynamic aspect of energy storage systems (ESS) operation in a new life cycle assessment (LCA) method to assess its potential environmental impacts
2. Integrate the external costs of electricity generation in the assessment of the ESS use phase through the expansion of the LCA method developed in sub-objective 1
3. Elaborate a framework for the evaluation of electricity generation in the short-term based on the LCA method developed in sub-objective 1

The methodological framework and its key elements are introduced in the subsequent section. Further details on the methodological developments, results and their interpretation are presented afterward in chapters 5 through 7 in the form of published or submitted articles.

3.4 Methodology

The methodological framework elaborated to achieve the goal of this research is represented in Figure 3.1 and the methodological steps to complete each specific objective are detailed in the

following sections of this chapter. These steps were applied to assess and compare the environmental impacts of lithium-ion (Li-ion) batteries operation in the electric grid of Normandy, France under various conditions.

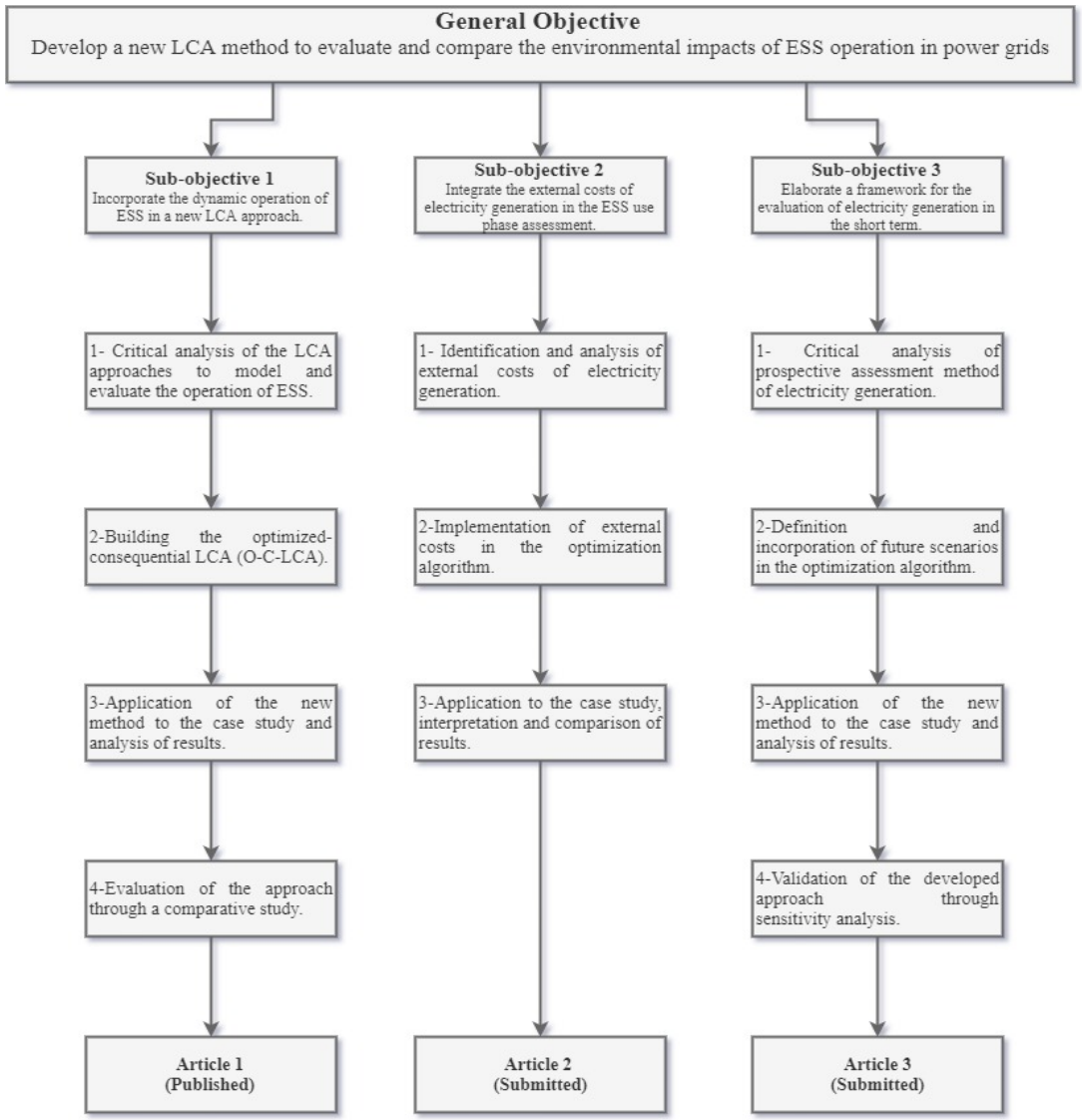

Figure 3.1 Overall methodological framework of the thesis

3.4.1 Meeting sub-objective 1: Incorporate the dynamic aspect of ESS operation in a new LCA method

The first sub-objective constitutes an essential methodological development to achieve the general goal of this thesis. A new LCA approach to model and evaluate the dynamic operation of new technologies such as ESS in power grids was proposed based on the gaps identified in the literature. In **step 1**, system optimization and LCA were both recognized as convenient methods to analyze electricity generation systems. To support grid-operators seeking the optimization of their generation and reduction of their environmental impacts, the need to combine these methods arises. In **step 2**, the integration of LCA and optimization into a new approach was proposed through soft-linking and resulted in the optimized-consequential LCA (O-C-LCA) (Elzein, Dandres, Levasseur, & Samson, 2018). The new method consists of using the output of the optimization algorithm as an input to the life cycle assessment. That is, the optimization step results in optimized electricity generation patterns, which are afterward evaluated using LCA. To build the optimization algorithm, we relied on the existing literature and defined a single-objective optimization problem that aims to minimize the total cost of electricity generation. By monetizing the impacts on climate change (CC), we incorporated the costs of electricity production and greenhouse gas (GHG) emissions into a total cost value. Data related to the case study were collected and the system constraints were defined based on the French transmission system operator (RTE) (RTE). We evaluated the potential environmental impacts from the operation of Li-ion batteries in the power grid of Normandy, France. The technical specifications of the existing power plants, their corresponding costs and emission factors, and the batteries information were all implemented in the optimization algorithm. The application to the case study was then performed in **step 3**. Once run, the optimization algorithm resulted in the optimized electricity generation pattern of the grid including the ESS. The environmental profile of this generation pattern was evaluated using LCA and the areas of potential improvement were identified. Furthermore, the O-C-LCA allowed the evaluation of the ESS use phase while accounting for the grid constraints. The consequences of ESS deployment on the operation of the different power sources were highlighted and the avoided climate change impacts due to the operation of the batteries were analyzed. Finally, in **step 4**, a comparative study was conducted and the ESS operation was estimated using two common methods. The first method used assumptions whereas the second used regional averages. The

avoided GHG emissions from the operation of the storage system in these two methods were compared to the results obtained using the developed O-C-LCA. The discrepancy in the finding was highlighted and recommendations for future applications were presented.

The steps followed to achieve this sub-objective fulfill the goal of the first journal article presented in Chapter 5.

3.4.2 Meeting sub-objective 2: Integrate the external costs of electricity generation in the assessment of the ESS use phase

The steps followed to reach the second sub-objective aim to expand the goal of the methodology developed in **sub-objective 1** and go beyond climate change impacts. While only the cost of GHG emissions was optimized in the objective function, we broadened the scope of the optimization to include additional costs and investigate the impacts of electricity generation at different levels. **Step 1** of this specific objective consists of identifying the different external costs of the power sector. The studies assessing the externalities of electricity generation were investigated to better understand how these costs are accounted for in the commonly applied methods. Electricity generation damages to human health (HH) and ecosystem quality (EQ) are generally monetized, which means specific costs are assigned for each impact category in order to be included in the total cost of generation (in this case study expressed in €/kWh). In **step 2,** the externalities corresponding to the operational power sources of the case study were determined and incorporated in the optimization algorithm. The algorithm was modified to include the cost of damages to HH and EQ in addition to the cost of electricity production and GHG emissions and the optimization objective, therefore, minimized the total cost of electricity generation. The modified algorithm was then applied to the case study in **step 3**. The optimized generation pattern accounting for externalities was compared to the operation of the historical grid and the optimized grid in terms of CC impacts only. The avoided impacts and potential cost reduction from the ESS operation were also evaluated to further highlight the importance of externalities.

The outcome of this sub-objective was integrated into a second journal article, presented in Chapter 6 of this thesis.

3.4.3 Meeting sub-objective 3: Elaborate a framework for the evaluation of electricity generation in the short-term

Sub-objective 3 constitutes the third step towards achieving the main goal of this thesis and helps demonstrate the applicability of the methodological framework to prospective studies. In this specific objective, the developed method was adjusted to fulfill an additional need identified in the literature which is the short-term environmental evaluation of power grids. In **step 1**, the commonly applied methods to model energy systems, assess the energy targets and evaluate the grids' environmental profiles were reviewed. The need for a new optimization method of reduced-complexity to evaluate the grids and support policymakers in their short-term decisions was highlighted. **Step 2** consists of adjusting the method developed in **sub-objective 1** to account for policies and energy goals. The Environmental Scenario Analysis (ESA) method was used to develop future scenarios based on data gathered from the French multiannual energy program and national low-carbon strategy (*Décret n° 2016-1442 du 27 octobre 2016 relatif à la programmation pluriannuelle de l'énergie* 2016; MTES). The increased installation of renewable energy sources, the decommissioning of fossil fuels and the addition of batteries as an ESS were evaluated. Scenarios based on national and regional energy targets were compared to highlight the importance of region-specific goals. In **step 3**, the adjusted method was applied to the case study and the results were compared to the historical grid operation to better understand the consequences of the different decisions. Finally, a sensitivity analysis was performed, and the optimization algorithm was modified and run according to the conditions of each scenario (**step 4)**. The resulting grid operation patterns were analyzed by means of an LCA and their impacts were compared to help policymakers identify the most beneficial practices supporting their strategies and make informed decisions.

The findings of this sub-objective completed the core of journal article 3, presented in Chapter 7 of this thesis.

CHAPTER 4 ORGANIZATION OF ARTICLES

Chapters 5 -7 constitute the core of this Ph.D. and details the research conducted to fulfill each sub-objective and their main findings (Figure 3.1). This section summarizes the scientific contribution of the thesis.

In Chapter 5, the optimized-consequential LCA (O-C-LCA), a novel assessment approach to model and evaluate the operation of new technologies was developed. It combined an optimization algorithm and LCA and was applied to evaluate the addition of a battery energy storage system (BESS) in the power grid of Normandy. The O-C-LCA allowed a detailed modelling of the batteries use phase and improved the evaluation of its consequences on the generation from the dispatchable power sources. Results emphasized the discrepancy in the estimation of avoided emissions from the BESS operation between the developed and common methods. The O-C-LCA was deemed convenient for the environmental evaluation of the BESS operation and assessment of new technologies in power grids.

This work was published in the *Journal of Cleaner Production*, 2018; IF 6.395 as an original article entitled: "**How can an optimized life cycle assessment method help evaluate the use phase of energy storage systems?".** The supplementary material published with this article is available in Appendices A and B.

In Chapter 6, the O-C-LCA was modified to include the external costs of the power sector. The monetized human health (HH) and ecosystem quality (EQ) impacts were introduced in the optimization algorithm to investigate their effect on the operation of the system. The modification of the O-C-LCA permitted a more holistic evaluation of electric grids by including emissions other than greenhouse gas emissions. The method was applied to assess the avoided environmental impacts and potential cost reductions from the BESS operation in the power grid of Normandy. Results showed that internalizing the cost of damage to HH and EQ in the total cost of electricity influences remarkably the operation of the generating sources and consequently alters the avoided impacts from the BESS use phase. The new approach improved the evaluation of the batteries operation and allowed the grid-operators to compare the energy generation alternatives while accounting for their total costs.

This work was submitted to *Science of the Total Environment*; 2019, IF 5.589 as a short communication entitled: "**Evaluating the avoided environmental impacts from the operation of energy storage systems"** and is currently under review.

In Chapter 7, the developed O-C-LCA method was used for the assessment of prospective scenarios. It was adjusted to include energy policies and emission targets in the constraints of the optimization algorithm. An environmental scenario analysis step was added to develop different cases and gathered the necessary data for the assessment including fuel costs, future emission taxes, short-term changes to the installed capacities and energy storage system specifications. The 2023 power grid of Normandy was modelled following the different scenarios and its environmental profiles were evaluated. Results improved the understanding of the different future measures and facilitated the identification of the most beneficial strategies. The developed method provided the policymakers and grid-operators with a tool of reduced-complexity to help them better develop and evaluate their energy policies and emission targets in the short-term.

This work was submitted to *Energy Conversion and Management*, 2019; IF 7.181 as a full-length article entitled: "**Environmental assessment of power grids in the short-term"** and is currently under review. The supplementary material submitted with this article is available in Appendices C and D.

The remaining contributions are listed in Appendix E.

The last two chapters of the thesis include a general discussion; Chapter 8 summarizing the implications of the completed work and defining some practical recommendations, followed by a conclusion in Chapter 9.

CHAPTER 5 ARTICLE 1: HOW CAN AN OPTIMIZED LIFE CYCLE ASSESSMENT METHOD HELP EVALUATE THE USE PHASE OF ENERGY STORAGE SYSTEMS?

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Abstract

The deployment of smart technologies such as storage systems is a requirement for the integration of renewable energy sources (RES) in today's grids. The increase in the share of renewable energy, mainly wind and solar power relies on the grid operators' capacity to offset intermittency and enhance the grids' flexibility, for which the most recommended solution is the deployment of energy storage systems (ESS). However, this type of addition to the grid will have consequences on current power sources operation and lead to changes in their environmental impacts. It is no longer possible to rely on temporally aggregated data, linear impact allocation assumptions or averaged emission factors to evaluate the ESS use phase. A more robust environmental assessment tool is therefore required. In light of this limitation, we propose an optimized consequential life cycle assessment (O-C-LCA) methodology applied to the Norman grid (France) for the year 2017. We optimally simulate the operation of lithium-ion batteries as an ESS within the grid by means of an optimization algorithm. The cost of electricity production, including greenhouse gas emissions through a price on carbon, is minimized, and the various generation sources are managed. A near-real ESS operation pattern is obtained as well. Afterward, we assess the environmental impacts of electricity generation using a retrospective consequential LCA. The results highlight the importance of time-variant data in the identification of the system's temporal hotspots. The life cycle optimization analysis illustrates the generation patterns and periods that

are most altered by (i) the minimization of electricity generation costs including greenhouse gas (GHG) emissions and (ii) the addition of an ESS. For this case, on average, 53% GHG emissions abatement results from the grid optimized operation and deployment of ESS, along with a total marginal operating costs reduction of 28%. Temporally-differentiated region-specific emission factors (EFs) are also recommended for enhanced assessment results. By including time-variant data and temporally-differentiated EFs, the developed method leads to an appropriate representation and a more accurate evaluation of the ESS use phase. It is therefore considered an effective tool for policy and decision makers regarding the impacts of ESS operation on the environmental profiles of power grids.

5.1 Introduction

Over the last decades, reliance on clean and renewable energy has become inevitable in order to cope with ever-increasing energy needs and avoid the further depletion of fossil fuels, increase of greenhouse gas emissions (GHG) and aggravation of climate change (Guney, 2011; Larcher & Tarascon, 2015). The renewable electricity mix is expected to be dominated by wind and solar power (Steinke et al., 2013), and the International Energy Agency estimates that, by 2025, these sources will account for 12% of the world's electricity output (IEA, 2015). However, these two renewable energy sources (RES) are expected to raise technical challenges at the electricity network level (Driesen & Belmans, 2006; Georgilakis, 2008) because of their intermittent nature and the daily and seasonal fluctuations in electricity demand (Guney & Tepe, 2017). Consequently, there is a need to drastically improve RESs forecasting (IRENA, 2016; McCrone et al., 2016) and deploy energy storage systems (ESS) (Mooney, 2015) to enhance the ability of grids to store energy at a large scale and low cost prior to shifting from a fossil-fuel based economy to a renewable-based one (Larcher & Tarascon, 2015).

ESSs are expected to play a vital role in future smart grids. These systems are critical to support RESs integration (Bradbury et al., 2014; Denholm, Paul et al., 2010; Krajačić et al., 2011) and offset intermittent production (Guney & Tepe, 2017; Telaretti & Dusonchet, 2017). They will enable load balance through the flexible dispatching of stored electricity (Bradbury et al., 2014) , help optimize grid operations (de Sisternes, Jenkins, & Botterud, 2016; IEA, 2014) and definitely

constitute a pillar of a low-carbon energy future (Grünewald et al., 2011; Guney & Tepe, 2017). However, the systems' operation may significantly impact the patterns and economics of electricity production, leading to changes in overall grid emissions (Hiremath et al., 2015). Therefore, policymakers require a convenient tool to assess the environmental consequences of their decisions to shift toward a greener energy system and deploy ESSs. The life cycle assessment (LCA) methodology is relevant for this type of evaluation and is a fundamental technique to support decision-making (Oliveira et al., 2015).

The existing LCA studies assessed the life cycle environmental impacts of various energy storage technologies (Guney & Tepe, 2017; Ma et al., 2014; Mohamed et al., 2017; Valente, Iribarren, & Dufour, 2017). Numerous authors focused on battery energy storage systems (BESSs) (Baumann et al., 2017; Longo et al., 2014; Sullivan & Gaines, 2012; Van den Bossche et al., 2006) and more particularly on the lithium-ion technology (Hesse, Schimpe, Kucevic, & Jossen, 2017; Peters, Baumann, Zimmermann, Braun, & Weil, 2017; Yu et al., 2012). Evaluating the life cycle footprint of this type of electrochemical storage is of great importance due to its wide range of applications, including EVs (e.g. (Ellingsen et al., 2014; Hawkins et al., 2012; Majeau-Bettez et al., 2011; Notter et al., 2010)), household (e.g. (Belmonte, Luetto, Staulo, Rizzi, & Baricco, 2017; Bila et al., 2016; Jing et al., 2012)), stationary (Rydh, 1999; Vandepaer et al., 2017; Weitzel & Glock, 2018) and electric utilities (Dunn et al., 2011; Subburaj et al., 2015; Vandepaer et al., 2018). At the grid-scale level, the addition of batteries facilitating the integration of RESs also affects the electricity production. Thus the environmental profile of the entire grid-mix changes. Currently, in the literature, there is a misrepresentation of the BESS operation leading to its inaccurate environmental evaluation. The use phase of batteries is either not investigated and the assessments are only from cradle-to-gate, based on theoretical assumptions and extrapolated from data of EV operation (e.g. (Ahmadi et al., 2014; Hiremath et al., 2015; Oliveira et al., 2015; Sternberg & Bardow, 2015)), or evaluated at the post-deployment level where the BESSs are already added to the grids and operational (e.g. (Consiglio et al., 2013; Dubarry et al., 2017; Koller et al., 2015)).

With the worldwide increasing number of deployed BESSs representing 62% of the entire storage system technologies in place (U.S.DOE, 2015), there is an immense need to better model their operation. Several studies evaluated their use phase (Crawford et al., 2018; Hesse et al., 2017; Schimpe, Naumann, et al., 2018; Weitzel & Glock, 2018) but mainly focused on the determination,

testing and investigation of their specificities, sizing, electrical performance and/or economic implications. Since the environmental impacts of the ESS operation heavily depend on the power sources that feed it (Turconi et al., 2013) and in order not to offset the advantages it brings to grids (Pehnt et al., 2008), the assessment of its use phase should be accounted for and must reflect its time-variant operation. To the best of our knowledge, from an environmental perspective, the operation of ESSs accounting for the actual grid constraints is either not considered or not suitably modeled in previous work. A new assessment method is therefore required to enhance their evaluation and more accurately assess the emissions resulting from the temporally-variable operation of power grids.

In this context, this paper proposes a time-variant optimized approach for the consequential life cycle assessment (O-C-LCA) method. The objective of the developed methodology is to overcome the limitations associated with the ESS use phase evaluation, since this LCA step can no longer be neglected, inaccurate or hypothetical. Knowing that the choice of emission factors (EFs) is critical and significantly influences the results of the ESS evaluation (Gordon & Fung, 2009; Messagie et al., 2014), this step is mainly performed through the development of temporally-differentiated region specific EFs. The novel approach is applied to a case study, which is the introduction of lithium-ion batteries as a storage system in the power grid of Normandy, France. Section 5.2 provides a detailed description of the case study. The process to conduct an O-C-LCA is comprehensively presented in Section 5.3, along with different emissions calculation methods. The section also details the methodology to evaluate different EFs, compare the marginal costs of generation and conduct the LCA of the ESS. Section 5.4 presents the results and discusses them along with the added value and limitations of the methodology. Finally, Section 5.5 provides a brief conclusion.

5.2 Case study

5.2.1 Norman grid

The electric grid in Normandy, France was chosen as a case study to demonstrate the applicability and relevance of the O-C-LCA. The power grid was selected for several reasons. First, the availability of detailed data (power generation by technology every 30 minutes). Data is required

to model the grid and obtain a comprehensive representation of the ESS operation. Second, the variability of electricity generation sources (both renewable and conventional). This feature makes the case study representative of numerous power grids around the world. Third, the characteristics of the region as a net exporter during an entire year (RTE). This feature highlights the importance of the ESS's role in storing and supplying cleaner electricity to nearby regions during peak demand periods. We assumed a virtual retrospective case study in which we evaluated the environmental impacts of the Norman grid for the year 2017 using electricity production data on a 30-minute basis to highlight the advantages of the new method.

Normandy traded electricity with four French regions: Bretagne, Centre Val-de-Loire, Île de France and Nord-Pas-de-Calais Picardie. Since every region has its own prices and generation technologies and the price of electricity on European markets highly influences the electricity trade, the accurate electricity evaluation was more challenging. Consequently, tracking and evaluating the environmental impacts of electricity generation was a painstaking task. For these reasons, the focus of this paper was the local generation, and all local demand was assumed to be satisfied by Norman power plants. Given that Normandy was a net exporter and that there was no authority over power generation in adjacent areas, the amount of electricity exported was considered as it was historically and added as a load in the simulations. Similarly, RESs power generation patterns were considered as they were back in 2017 since these sources are not dispatchable and cannot be controlled by the system operators. As such, the power generated by the RESs was harvested and the ESS, nuclear and thermal sources were then dispatched, as explained in Section 5.3.2, to supply the remaining load and ensure power balance.

5.2.2 Batteries in power grids: lithium-ion

There are five main types of energy storage technologies of various capacities, including electrochemical, electromechanical, thermal, hydrogen and pumped hydro (U.S.DOE, 2015). Among the available systems, batteries, a sub-category of the electrochemical technologies, are gaining an importance as storage for power grids and deployed gradually (McCrone et al., 2016; Mooney, 2015). Lithium-ion batteries in particular already dominate the mobile application sector and are steadily moving toward stationary energy systems. Hiremath et *al.* (Hiremath et al., 2015) recommended their deployment for stationary grid operation due to their high round-trip efficiency.

These batteries are also a mature technology characterized by its safe operation (Dunn et al., 2011) and long cycle life (Reddy & Linden, 2011) as compared to other types of batteries. In light of these benefits, a fictive scenario was considered to investigate their impact on power grids. In the Norman grid, 250 Li-ion battery units with 80% efficiency were considered available. These batteries delivered 500 MW, the equivalent of approximately 5.6% of the total non-RESs maximal generation. The efficiency of the batteries was determined based on the literature and considered as a reasonable value between the efficiencies in various studies (Ahmadi et al., 2014; Ibrahim, H, Beguenane, & Merabet, 2012; Sbordone, Di Pietra, & Bocci, 2015; Schimpe, Piesch, et al., 2018). As for the sizing of the ESS, it is a widely researched topic and requires comprehensive analyses. But since this is outside of the scope of this paper, and to facilitate calculations, the capacity of the batteries was chosen based on historical data by calculating the difference between the minimum generation of all the available technologies and the lowest consumer demand. The minimum generation was the amount of power these sources can produce before either being shut down or causing financial deficit. With the consumer demand being lower than the minimal generation, there was an excess of produced electricity and this amount therefore helped us set the capacity of the batteries. Such cases occur whenever the demand is extremely low and it is costlier to shutdown and start-up the generators than to leave them on for a certain period.

Like the remaining dispatchable power sources, the batteries were operated (charged and discharged) to satisfy the consumer demands. We compared the optimized electricity production with an ESS (simulated grid operation) and without it (historical grid operation) to retrospectively assess the impact of ESS deployment in 2017. Furthermore, this case study aimed to illustrate the developed approach. It should not be limited to the evaluation of Li-ion batteries and it could also be applied to different ESS technologies in other geographical contexts.

5.3 Methodology

5.3.1 Optimized-consequential LCA

There are two major LCA approaches: the attributional (A-LCA) and the consequential (C-LCA) (Guinée, Jeroen B, 2002; Tillman, 2000). The purpose of the LCA determines the methodology to be used (Brander, Matthew, 2016; Consequential-lca, 2015; Ling-Chin, Heidrich, & Roskilly,

2016). The consequential approach was convenient for our study since it aims to describe how environmentally relevant physical flows respond to possible changes in the life cycle of a system (Ekvall, Tomas & Andrae, 2005). Furthermore, we were interested in generating and optimizing process alternatives; thus, the combination of a time-variant analysis and an LCA by means of an optimization method was highly relevant.

This paper proposes a novel approach to evaluate the impacts associated with the ESS use phase in the Norman grid context. The new method overcomes the limitations of extrapolations and assumptions. Even though the concept of optimization within the LCA methodology has been presented previously (Gong & You, 2017), to the best of our knowledge, the representation of the temporal variability aspect was still missing. Therefore, we developed a two-step LCA methodology: an optimized-consequential LCA described here and illustrated in Figure 5.1.

The **first step** of the new methodology investigates the base case scenario: historic grid operation without ESS. It consists of gathering historical data of the Norman grid operation in 2017, compiling inventories and using temporally-differentiated EFs to compute the environmental impacts of the grid. This step facilitates the evaluation of the status quo of the system under assessment and therefore, serves as a basis for the comparison with the system including an ESS.

The consequences of operating an ESS in the Norman grid are introduced in the **second step** of the new approach**.** We rely on historical data, gather additional data and set new assumptions to build a scenario that estimates the impact of batteries on the grid. We assume that grid operators are interested in minimizing the power grid operating costs, including the cost of emissions (Bernal-Agustín, Dufo-López, & Rivas-Ascaso, 2006; Dufo-López & Bernal-Agustín, 2008; Dufo-López et al., 2011; Pelet, Favrat, & Leyland, 2005). We then add and optimally operate the ESS. Hence, we rely on an optimization algorithm accounting for the current system and ESS limitations (see section 5.3.2) to obtain a time-variant optimized grid operation pattern including the ESS operation profile. We compare it afterward to the historical pattern developed in the first step to identify the consequences of the batteries addition on the electricity generation and on its environmental profile.

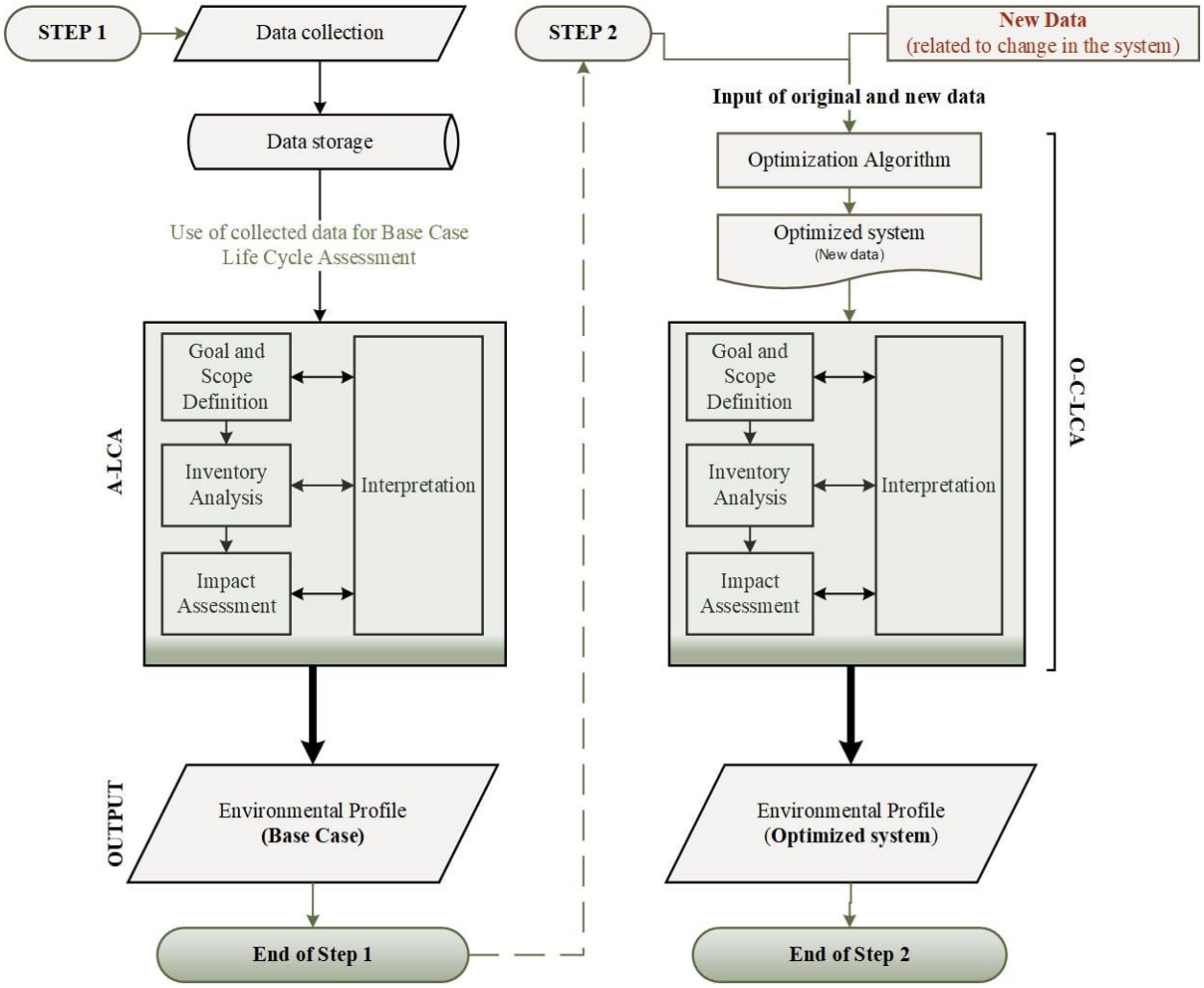

Figure 5.1 Two-step LCA approach: optimized-consequential LCA (O-C-LCA)

In this paper, we highlight the impacts of the ESS operation phase. The formulation of the optimization algorithm through the determination of its objective and constraints is introduced in Section 5.3.2. The approach to carry the LCAs is then presented in Section 5.3.3. Section 5.3.4. summarizes the different sensitivity analyses. It describes the scenarios for the EFs comparison, the ESS marginal cost evaluation, and the ESS assessment.

5.3.2 Optimization

Once implemented in the grid, new technologies, like ESSs, are assumed to be operated optimally. This is why the operation of Li-ion batteries deployed in the Norman grid was obtained using an optimization algorithm. The choice of the optimization method was based on literature (Azapagic

& Clift, 1999; Moghaddam, Seifi, Niknam, & Pahlavani, 2011; Yamashita, Niimura, Yokoyama, & Marmiroli, 2010). The optimization algorithm was formulated according to the equations presented later in this section and then solved using Matlab by relying on the fmincon function (Sequential Quadratic Programming algorithm). The selection of algorithm depended on its efficiency in terms of both memory usage and speed; see (MathWorks) for further details. The optimization step resulted in electricity production patterns that were representative of locally installed capacities and consumption levels. These data corresponded to the optimal power generation that minimizes operating costs including those related to CO_2 emissions while taking into consideration the deployment of ESS in the grid. Thus, the algorithm guaranteed optimality under the study constraints. When formulating the objective function, we assigned a cost to the emissions. The solution to the problem was cost minimization, which rendered the problem more of a single-objective problem and then justified the single optimal solution instead of a range of optimal options.

As an input to the optimization algorithm, we considered historical generation from RESs along with historical electricity demand. These RESs represented the non-dispatchable production, and the power they generated cannot be controlled by network operators since it varied according to weather conditions and geographic location. The output of the algorithm was the generation patterns of dispatchable technologies, namely nuclear, coal and natural gas, in addition to the ESS. The technologies considered as RESs were solar and wind power. Based on historical Norman data, the maximum contribution of bioenergy and hydropower to the total generation was 0.9%. Being that small and having negligible installed capacities as compared to nuclear and fossil fuels, these sources were exceptionally classified as non-dispatchable.

The literature was used to 1) implement the optimization algorithm, 2) allocate the optimal power generation set points, 3) satisfy equality and inequality boundaries and 4) define the objective function, namely the cost minimization, and 5) establish the power system constraints (Moghaddam, Seifi, & Niknam, 2012). The capacities of locally available power sources and the storage system were also set. As for the active power, energy limits, costs, and EFs, they were either retrieved from (RTE) or assumed based on historical data. Historical electricity production data was available on a 30-minute basis (RTE), which was the period considered for the

optimization. Consumer demand was supplied by the RESs first. The remainder of the load was supplied by the ESS (if charged) and the other dispatchable technologies.

The operating costs included the costs of fuel, generating unit start-up and shutdown, emissions and electricity trade. The objective function aimed to minimize the costs to find the optimal solution (i.e. an electricity generation pattern) for all these criteria. The single cost function was represented by the following equation:

Min f(X) = $\sum_{t=1}^{T} Cost^{t}$

$$= \sum_{t=1}^{T}\{ \sum_{i=1}^{N_g}[\frac{u_{Gi}(t)P_{Gi}(t)GC_{Gi}(t)}{(t)-(t-1)} + u_{Gi}(t)P_{Gi}(t)EF_{Gi}(t)CC]$$

$$+ \sum_{j=1}^{N_s}[\frac{u_{Sj}(t)P_{Sj}(t)GC_{Sj}(t)}{(t)-(t-1)} + u_{Sj}(t)P_{Sj}(t)EF_{Sj}(t)CC]$$

$$+ [\frac{P_{Grid}(t)GC_{Grid}(t)}{(t)-(t-1)} + P_{Grid}(t)EF_{Grid}(t)CC]\}$$

Where:

- Generators are denoted by the letter G, and S designates storage systems.
- $u_{Gi}(t)$ and $u_{Sj}(t)$: status of unit i/j at time t, either 1 if the unit is on or 0 if it is off
- P_{Gi} and P_{Sj} *:* the active power of the ith generator and jth storage device at time t in (MW)
- GC_{Gi} and GC_{Sj}: generation costs of the ith generator and jth storage device at time t in (€/MWh)
- P_{Grid} *:* the active power which is bought/sold from/to the utility at time t (representing the trade) in (MW)
- GC_{Grid}: the average generation cost of the utility at time t in (€/MWh)
- $EF_{Gi}(t) = CO_{2_{DG_i}}$: Emission factor of CO_2 emissions from the ith distributed generator (DG) at time t expressed in (tCO_2/MWh)

- $EF_{Sj}(t) = CO_{2_{Storage_i}}$: Emission factor of CO_2 emissions from the jth storage at time t expressed in (tCO_2/MWh)
- $EF_{Grid}(t) = CO_{2_{grid}}$: Emission factor of CO_2 emissions from the utility at time t expressed in (tCO_2/MWh)
- *CC*: Carbon Cost expressed in (€/tCO_2)
- T: Total number of hours
- N_g: Total number of generators
- N_s: Total number of storage systems

We used OpenLCA (version 1.7.0) as the LCA software, IMPACT2002+ (version 2.2) as the impact assessment method and the ecoinvent database (version 3.2) to calculate the EFs of producing 1 kWh of electricity from each technology available in the case study. In 2014, the French parliament introduced the carbon tax on gas, heavy fuel oil and coal (WorldBank). For the year 2017, the cost of carbon emissions was set at 30.5 €/tCO_2 (WorldBank, 2017).

In this paper, the ESS was an electrochemical system (battery) that does not have a cost or emits CO_2 when operated. The cost and emissions resulting from the generation of electricity to charge the battery are only attributed to the power sources and not to the battery in order to avoid double counting. Thus, the value attributed to EF_{Sj} was null. However, when it comes to other types of ESSs, their operation generates additional costs that should be accounted for. Similarly, for the remaining life cycle stages of the Li-ion batteries, their emissions were not 0 and should be computed when evaluating the storage systems to make a more holistic decision regarding their benefits (see Section 5.3.4.3. for further details).

The optimization problem was subjected to three main constraints presented here.

- **<u>Constraint 1:</u> power balance**

Total consumer demand must be met. Otherwise, there will be outages. Therefore, the electricity produced should be at least equivalent to demand.

Supply = Demand

$\sum_{i=1}^{N_g} P_{Gi}(t) + \sum_{j=1}^{N_s} P_{Sj}(t) + P_{Grid}(t) = \sum_{k=1}^{N_k} P_{Lk}(t)$

Where P_{Lk} : the amount of kth load level (MW)

- **<u>Constraint 2:</u> active power limits**

When supplying the consumers' demand, the amount of electricity produced cannot exceed the installed capacities of the power plants. Hence, the generation should remain between the allowable minimum and maximum of every source based on its power bounds.

$P_{Gi,min}(t) \leq P_{Gi}(t) \leq P_{Gi,max}(t)$

$P_{Sj,min}(t) \leq P_{Sj}(t) \leq P_{Sj,max}(t)$

$P_{Grid,min}(t) \leq P_{Grid}(t) \leq P_{Grid,max}(t)$

Where:

- $P_{Gi,min}(t)$ & $P_{Gi,max}(t)$: the minimum active power and the maximum power generation of the ith DG (MW)
- $P_{Si,min}(t)$& $P_{Si,max}(t)$: the minimum active power and the maximum power generation of the jth storage (MW)
- $P_{Grid,min}(t)$ & $P_{Grid,max}(t)$: the minimum active power and the maximum power generation of the utility (MW)

- **<u>Constraint 3:</u> battery limits**

Batteries are limited by the amount of electricity they can store/release and cannot be charged or depleted over their capacity.

$$W_{ess,t} = W_{ess,t-1} + \eta_{charge} P_{charge}(\Delta t) - \frac{1}{\eta_{discharge}} P_{discharge}(\Delta t)$$

$W_{ess,min} \leq W_{ess,t} \leq W_{ess,max}$

$P_{harge,t} \leq P_{charge,max}$

$P_{discharge,t} \leq P_{discharge,max}$

Where:

- $W_{ess,t}$ & $W_{ess,t-1}$: the amount of energy stored inside the battery (MWh)
- $\eta_{charge}(\eta_{discharge})$: efficiency of the battery during charge (discharge) process (%)
- $P_{charge}(P_{discharge})$: the permitted rate of charge (discharge) during the period of time Δt (MWh)
- $W_{ess,min}$ & $W_{ess,max}$: the lower and upper limits on the amount of energy storage inside the battery (MWh)
- $P_{charge,max}$ ($P_{discharge,max}$): the maximum rate of battery charge (discharge) (MWh)

Normandy was an exporter region, and the amount of exported power was added to the total demand that must be supplied by the various resources. Additional information on the data required for calculations is included in Appendix A.

By the end of this step, the optimized grid operation by fuel type for every 30 minutes of the year 2017 was obtained and analyzed based on the consequential LCA method.

5.3.3 Life Cycle Assessment

5.3.3.1 Consequential LCA of the grid

LCA is a standardized technique that entails four main steps, in compliance with the 14040 and 14044 International Standardization Organization (ISO) standards (ISO, 2006a, 2006b). These steps are detailed here.

5.3.3.1.1 Goal and scope

The objective of this C-LCA was to model the differentiated environmental impacts of the electricity generation with ESS deployment in the Norman grid. To that end, the marginal sources of electricity (i.e. the sources of electricity that adapt their generation capacity to the electric needs in the presence of ESS) were modeled. The studied system was the entire Norman power grid. As a part of the two-steps methodology, the obtained environmental profile was to be compared to the base case assessment results as well. The functional unit (F.U.) was to fulfill local consumer

demand for electricity and the demand of neighboring regions retrospectively, as they were in 2017, in MWh, every 30 minutes, over the entire year.

5.3.3.1.2 Life cycle inventory

The optimization step resulted in electricity generation patterns by technology type for every 30 minutes. The ecoinvent database (version 3.2) was used to model the marginal technologies identified based on historical data. Table 5.1 summarizes the ecoinvent processes used to model electricity generation. Several ecoinvent processes corresponded to the same French technology but not all of these technologies were available in Normandy (e.g. oil). Therefore, the table was adapted to represent local sources. As for the cases in which there was more than one type, the technologies were assigned different weights based on their installed capacities in Normandy.

Table 5.1 Electricity generation technologies available in Normandy and considered in the ecoinvent database

Energy source	**Ecoinvent process**	**% from installed capacities**
Nuclear	electricity, high voltage | electricity production, nuclear, pressure water reactor – FR	80.2
Coal	electricity, high voltage | treatment of coal gas, in power plant – FR	11.1
	electricity, high voltage | electricity production, hard coal – FR	
	electricity, high voltage | treatment of blast furnace gas, in power plant – FR	
Natural gas	electricity, high voltage | heat and power co-generation, natural gas, conventional power plant, 100MW electrical – FR	3.8

	electricity, high voltage | electricity production, natural gas, conventional power plant – FR	
	electricity, high voltage | electricity production, natural gas, combined cycle power plant – FR	
Hydro	electricity, high voltage | electricity production, hydro, run-of-river – FR	0.3
Wind	electricity, high voltage | electricity production, wind, >3MW turbine, onshore – FR	3.5
	electricity, high voltage | electricity production, wind, <1MW turbine, onshore – FR	
	electricity, high voltage | electricity production, wind, 1-3MW turbine, offshore – FR	
	electricity, high voltage | electricity production, wind, 1-3MW turbine, onshore – FR	
Solar	electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted | electricity, low voltage | cut-off, U FR	0.6
	electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted | electricity, low voltage | cut-off, U FR	
	electricity production, photovoltaic, 570kWp open ground installation, multi-Si | electricity, low voltage | cut-off, U FR	
Biomass	electricity, high voltage | heat and power co-generation, biogas, gas engine – FR	0.5

	electricity, high voltage | heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014 – FR	

5.3.3.1.3 Life cycle impact assessment

The evaluation was performed at the endpoint level with IMPACT2002+, where only four categories were of concern: Climate Change (CC) expressed in kilograms of carbon dioxide equivalent (kg CO_2 eq); Ecosystem Quality (EQ) in potentially disappeared fraction species per square meter per year (PDF/m^2/yr); Human Health (HH) in disability-adjusted life years (DALY) and Resources (R) in surplus of energy required to extract new raw materials (MJ primary). The assessment was based on each marginal technology and the amount of electricity it generated.

5.3.3.1.4 Identification of marginal electricity and its marginal sources

The approach followed by Dandres et *al*. in (Dandres, T. et al., 2017) was used to identify the marginal sources of electricity.

1. The power generation from a specific technology i at time t_1 and t_2 were identified and the difference in the generation between t_2 and t_1, being $\Delta P_i = P_{i,t2} - P_{i,t1}$ was calculated.
2. The sum of power generation from all the technologies at t_1 and t_2 were identified along with the difference in the generation between t_2 and t_1, being $\Delta P_{Total} = P_{Total,t2} - P_{Total,t1}$
3. The marginal share of technology i was therefore calculated: Marginal share $_i = \frac{\Delta Pi}{\Delta PTotal} \times 100$

To build the marginal mix on a 30-minute basis, the marginal share of each available technology over the entire study time was calculated. This approach assumed that all marginal technologies are affected simultaneously by the operation of the ESS. If this study was not retrospective, the determination of marginal sources would not have been possible by solely relying on historical data. Rather, it would have required market models as in (Gong & You, 2017).

5.3.3.1.5 Calculation of marginal GHG emission factors

The marginal GHG EFs on a 30-minute basis were calculated based on the literature (Dandres, T. et al., 2017) as follows.

1. For technology i: Marginal EF_i = Marginal share $_i$ × EF_i at the specific time t
2. For the entire grid: Marginal $EF_{Total} = \sum MarginalEFi$

5.3.3.2 A-LCA of electricity generation

We compared the operation of the historical and optimized grids using A-LCA to emphasize how the technologies were affected by the addition of ESS over time. This step was performed according to the following equation:

$$\Delta P = P_{Gi-baseline}(t) - P_{Gi-OptwithESS}(t)$$

Where:

ΔP: change in power generation

$P_{Gi-baseline}(t)$: historical power generation at time t (MW)

$P_{Gi-OptwithESS}(t)$: power generation of the optimized grid deploying ESS at time t (MW)

5.3.4 Sensitivity analysis

5.3.4.1 EF comparison

We assessed the optimized grid operation using the attributional approach by means of three different EFs. The resulting CO_2 emissions were compared to highlight the added-value of temporally-differentiated EFs specific to Normandy in the computation of emissions and accuracy of results.

The three modeled EFs were as follows:

a- Time-variant technology EF specific to Normandy calculated by multiplying the generation of each technology in the Norman grid by its corresponding EF at 30-minute intervals.

b- Time-variant technology EF specific to France calculated by multiplying the generation of each technology in the French grid by its corresponding EF at 30-minute intervals.

c- Averaged French EF calculated by multiplying the total generation at each 30-minute interval by the French averaged EF of 0.07093 tCO_2/MWh retrieved from (Brander, Matthew , Sood, Wylie, Haughton, & Lovell, 2011).

5.3.4.2 Comparison of the marginal costs of generation

For the operating costs comparison, the marginal cost of generation was compared for the dispatchable sources, namely nuclear and thermal sources. That is, the marginal share of the technology considered was multiplied by its cost of generation before computing the averaged cost value over all of 2017. Since the marginal sources differed between the base case and optimized case with ESS, the resulting marginal costs also changed. This comparison aimed to emphasize the economic gains during the electricity generation process once an ESS is deployed and optimally operated.

5.3.4.3 LCA of the ESS

5.3.4.3.1 Use phase of ESS

For the ESS use phase assessment, we compared the annual saved CO_2 emissions obtained using three different methodologies: A) the time-variant optimized approach developed in this study; B) the approach presented by Majeau-Bettez et *al.* in (Majeau-Bettez et al., 2011) and C) the approach proposed by Sternberg & Bardow in (Sternberg & Bardow, 2015).

The steps to compute the saved emissions are detailed here.

A) For the time-variant optimized approach:

1) divide the ESS generation over the sum of generation from all sources to compute the

ESS share of generation;

2) multiply the generation from each source by its corresponding EF to compute the grid CO_2 emissions;

3) multiply the obtained ESS share of generation by the total grid emissions at each time interval to obtain the ESS saved emissions at every period and

4) sum all the avoided emissions over the entire year and divide them by the number of battery units.

B) The Majeau-Bettez et *al.* approach is denoted as GMB operation. The authors considered the European EFs to calculate the grid emissions before computing the saved emissions from the batteries. Here are the steps followed:

1) divide the ESS generation over the sum of generation from all sources to compute the ESS share of generation;

2) multiply the European EFs by the total generation at every time interval to compute the grid CO_2 emissions;

3) multiply the obtained ESS share of generation by the total grid emissions at each time interval to obtain the ESS saved emissions at every period and

4) sum all the avoided emissions over the entire year and divide by the number of battery units.

C) The Sternberg & Bardow approach is abbreviated as Assumed operation. The authors assumed that the power produced by the ESS substitutes power from gas turbines with 40% efficiency. The computation of saved emissions has the following steps:

1) calculate 40% of thermal power generation at every time interval and consider it as the ESS power generation;

2) divide the ESS generation over the sum of generation from all sources to compute the ESS share of generation;

3) multiply the generation from each source by its corresponding EF to compute the grid CO_2 emissions;

4) multiply the obtained ESS share of generation by the total grid emissions at each time

interval to obtain the ESS saved emissions at every period and

5) sum all the avoided emissions over the entire year and divide by the number of battery units.

The electricity sources feeding the ESS differed between the three methodologies; hence, the estimation of avoided emissions from the ESS use phase changed. Since these studies were not directly comparable, the annual saved emissions were compared to emphasize the benefit of the newly developed method.

To obtain the saved CO_2 from the use phase of 1 kg of battery unit, it was calculated by dividing the total saved emissions in 2017 by the total number of units. Every module weighed around 39.5 kg, based on an industrial value provided for the Seanergy battery modules from SAFT batteries (SAFT). The saved emissions from the operation of 1 kg of battery pack were then compiled.

5.3.4.3.2 Manufacturing and end-of-life of ESS

To assess the battery pack manufacturing, we relied on the parametrized Li-ion life cycle inventory of Peters & Weil in (Peters & Weil, 2018) and assumed a 10 years lifetime of a battery (ACS, 2013). The choice of this adapted inventory was considered convenient for our study since it is well founded and thus helped us reduce the uncertainties in this assessment. The F.U. considered for this step was “production 1 kg of Li-ion battery pack”. For the end-of-life (EoL) of Li-ion batteries at grid-scale, there was a lack of precise information. Currently, there are flawed waste legislation and very low collection rates of batteries. Hence, this type of BESSs is most commonly incinerated and landfilled (Zacune, 2013). The F.U. chosen was “incineration of 1 kg of Li-ion battery pack”. We then calculated the resulting annual CO_2 emissions from 1 kg battery pack manufacturing and incineration.

Appendix B details the components considered in the LCA of batteries, the assessment values, and the calculation steps.

5.4 Results and discussion

The methodology outlined in this paper was evaluated for the year 2017. January, which has the highest historical demand in Normandy, was mainly represented (see Figure 5.2- 4.4) since during this period the ESS interfered the most. Moreover, to facilitate visualization and better reflect the temporal granularity of the data, only selected days were depicted.

With the introduction of ESS into the grid, the power sources supplying the marginal additional demand were adjusted, hence changing the marginal EFs. This variation in marginal EFs between the base and optimized cases is represented in Figure 5.2. Figure 5.3. highlights the benefits of the addition of the storage system in terms of emissions reduction. Since the operation of power grids with and without an ESS differed, Figure 5.3 illustrates the difference in the resulting CO_2 emissions. The operation of ESS also affected the electricity production from thermal and nuclear power sources. Thus, their annual average generation was compared between the base and optimized cases in Figure 5.4. Furthermore, the choice of EFs significantly impacts the calculation of emissions. In order for the grid emissions to be computed accurately, these EFs must be representative of the study area and available technologies. This is why the evaluation of optimized grid emissions was carried out using different emission factors in Figure 5.5 and the resulting diagram highlights the importance of the temporally-differentiated EFs specific to Normandy.

5.4.1 Assessment of the marginal EFs

The variation of marginal temporally-differentiated emission factors between the base case, optimized grid with ESS and ESS from January 2 to 5, 2017, is illustrated in Figure 5.2. The graph provides insight into marginal grid operation by adequately representing the temporal granularity of power system operation. It also makes it possible to emphasize the periods of ESS contribution in the optimized case. During certain periods in the year, the ESS discharged and replaced the conventional power sources. These periods are depicted by nearly flat segments in the plot of the marginal ESS EFs (dotted line). In other words, the high values of EFs in the base case result from an increased share of production from fossil fuels to meet the increased demand. This is when the ESS interfered in the optimized case and replaced coal and natural gas, resulting in lower EFs.

Conversely, the low base case EFs at certain times indicate a lower demand period, and this is when the ESS charged. Furthermore, the curves of the optimized grid and ESS generally follow a similar pattern. This propensity is justified by the fact that the ESS is among the main contributors to the marginal EF of the optimized grid and thus impacts its values.

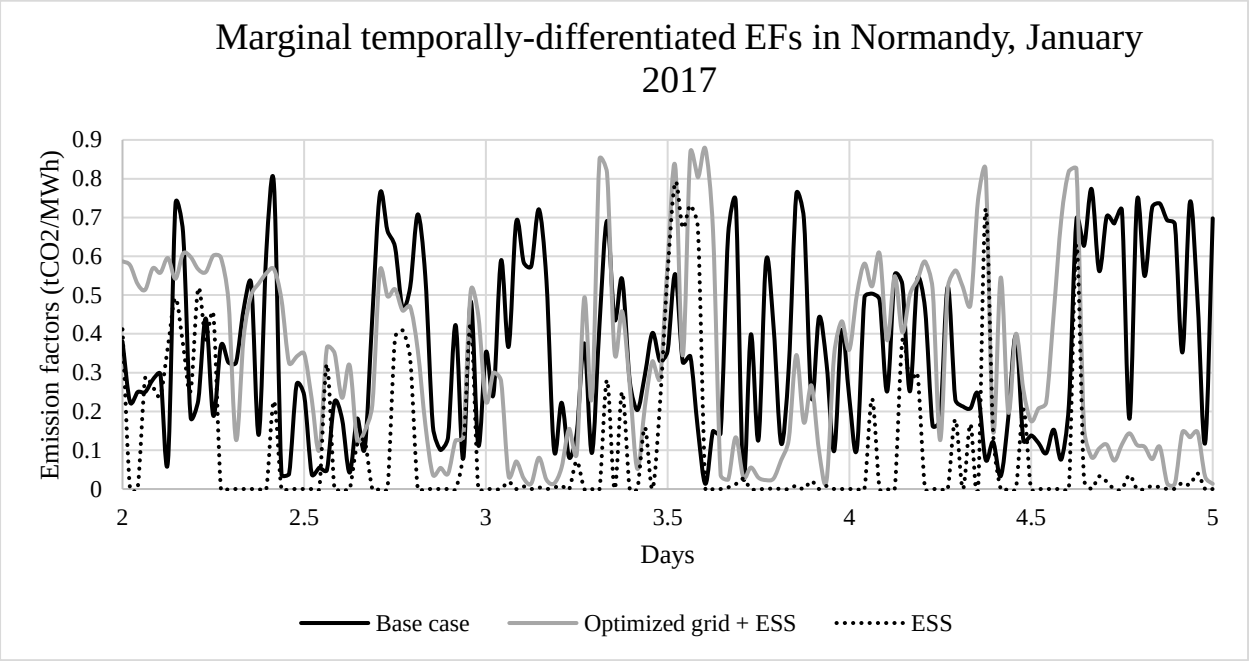

Figure 5.2 Variation of marginal EFs between ESS, the optimized grid with ESS and the base case grid from January 2 to 5, 2017

Based on the model and its assumptions, it is suggested that the optimization of power sources could lead to reductions in the overall grid operating costs, including the costs of CO_2 emissions. The marginal cost of electricity generation over the entire year was reduced by approximately 28% when the grid included an ESS and was optimally operated. This reduction is justified by the fact that nuclear power in France is a mature technology with a fairly inexpensive operation cost and a lower EF as compared to thermal power sources. Furthermore, batteries were assumed to have no cost of operation. Hence, their addition is considered economically beneficial at the electricity generation level.

5.4.2 Assessment of the grid using A-LCA

After highlighting the consequences of ESS deployment at the marginal level, Figure 5.3. illustrates the emissions from electricity generation in Normandy in January 2017 for two scenarios: the base case and the optimized grid including an ESS. The graphs prove that the base case grid and optimized grid followed a similar pattern of electricity production. That is, the increase and decrease in emissions in the two grids occurred at the same periods, yet the optimized grid deploying an ESS emitted remarkably less CO_2 (approximately 53% reduction in annual emissions and 59% reduction in January emissions). This reduction could potentially be achieved by deploying ESS in the Norman grid and optimizing its operation. This optimization of power generation required an increase in the electricity production from nuclear sources by, on average, 6% annually to substitute the generation from fossil fuel by 62%, as illustrated in Figure 5.4.

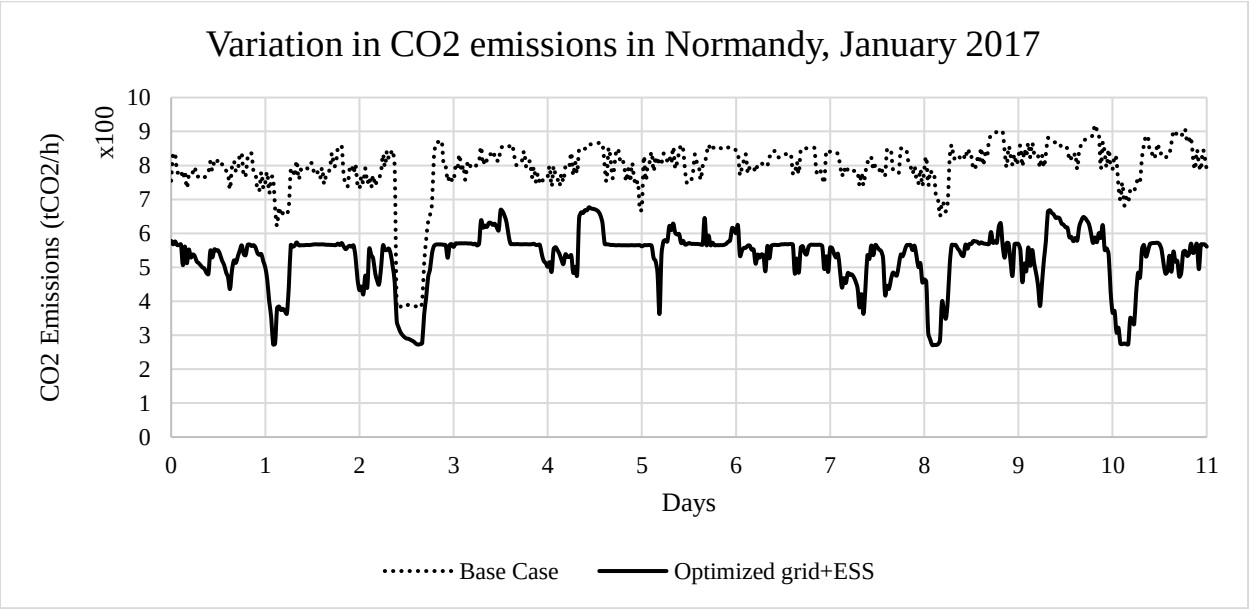

Figure 5.3 Variation in emissions between the optimized grid with ESS and base case grid

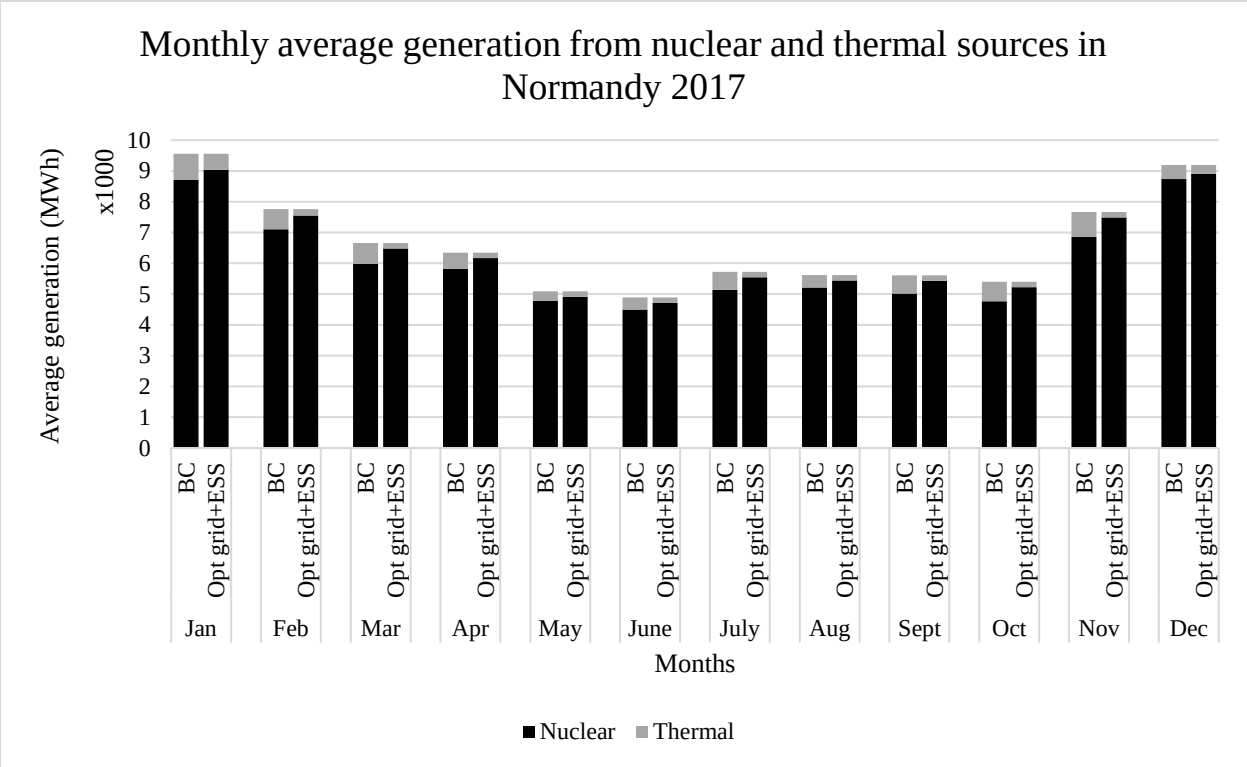

Figure 5.4 Variation in monthly average generation shares from nuclear and thermal sources in Normandy in 2017 between the base case grid and optimized grid with ESS

5.4.3 Comparison of various emission factors

The EFs used in the LCA methodology are advantageous since they are not limited to a single life cycle phase. In the power sector, the life cycle EFs account for the various steps, such as power plant construction, fuel extraction and even RESs conversion to electricity (Şengül, Bayrak, Aydınalp Köksal, & Ünver, 2016). The choice of EFs significantly influences the results of the assessments, as demonstrated by several authors, including (Gordon & Fung, 2009; Messagie et al., 2014), and confirmed by the results in Figure 5.5. A common practice to assess the electric grid environmental impacts is relying on annual averaged EFs for the country and multiplying them by the total generation at every time interval. Yet, depending on a single value for the EF results in inaccurate estimations, as shown in Figure 5.5, where the real emissions were overestimated and their variations over the entire period were relatively masked. In this study, region-specific temporally variable EFs were chosen over national temporally-variable EFs. The two curves did not overlap, and the temporally variable EFs for France overestimated the actual emission values

of the Norman grid. This difference was attributed to the electricity generation technologies available in France and missing in Normandy. This disparity was amplified because Normandy was a net exporter region and is therefore unaffected by the grid mixes in neighboring regions. Over the entire year 2017, for the base case grid, the French temporally-variable EFs and the French average EF underestimated the CO_2 emissions by 17% and 14%, respectively. However, for the optimized grid deploying an ESS, the EFs overestimated the emissions by about 80%. Therefore, to have an accurate evaluation of the ESS use phase, we recommend that the factors be specific to the area under assessment and representative of the locally available technologies.

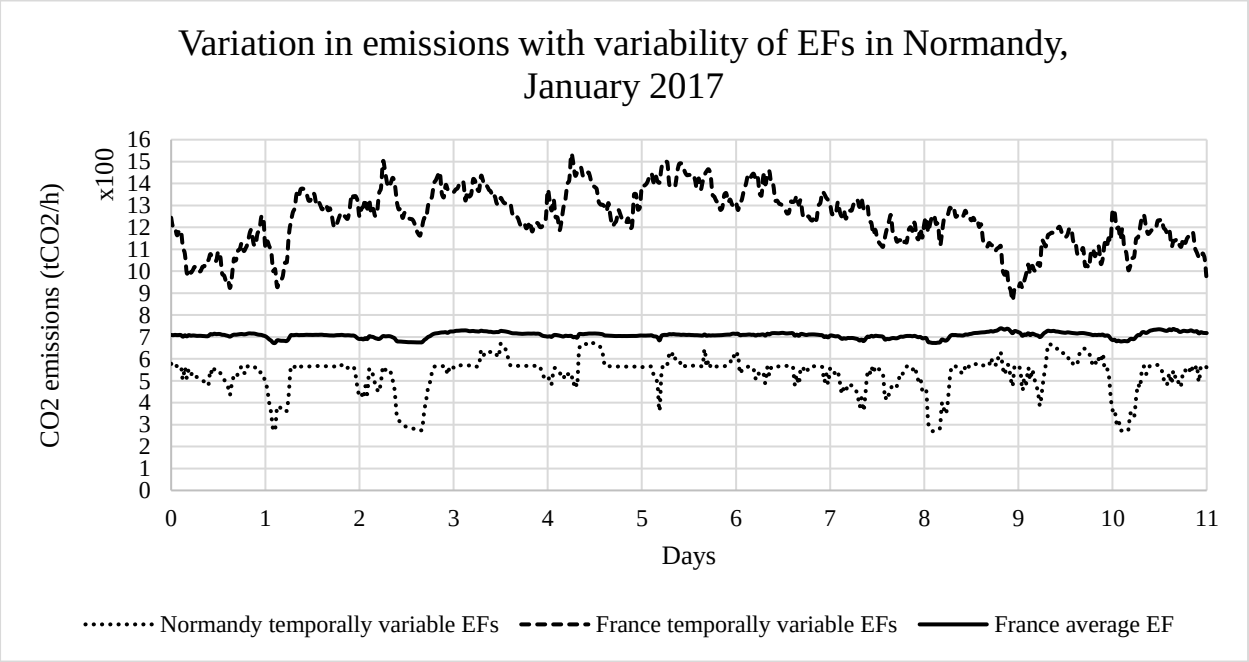

Figure 5.5 Variation in emissions with the variation in EFs in the optimized grid in the first 11 days of January 2017

5.4.4 ESS evaluation

5.4.4.1 Comparison of the ESS use phase

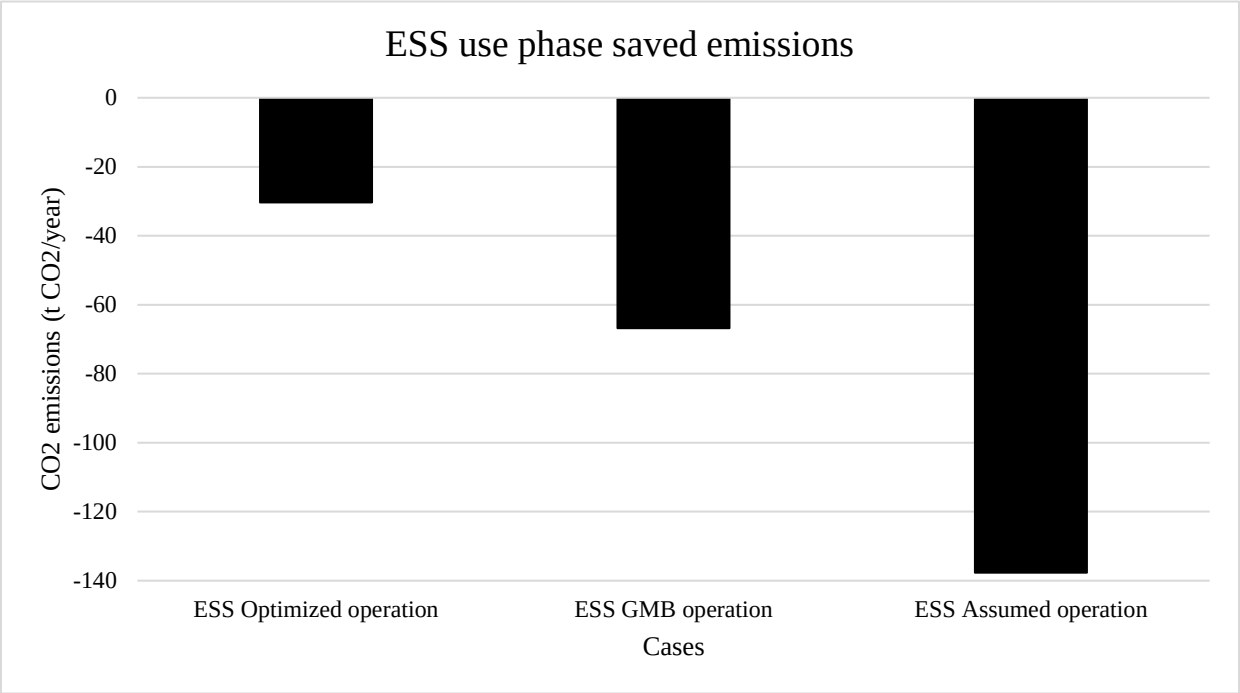

Figure 5.6 Comparison of the saved emissions from the ESS operation computed for three different use phase evaluation methods

To better understand the benefits of the developed approach, the saved CO_2 emissions from the ESS operation were compared and Figure 5.6 illustrates the results. Those emissions were computed according to three different methodologies: the ESS Optimized operation, the ESS GMB operation, and the ESS Assumed operation, described thoroughly in Section 5.3.4.3. Figure 5.6. indicates that both approaches overestimate the CO_2 savings resulting from the BESSs operation obtained by means of the Optimized method.

The GMB operation results were about twice the optimized approach saved emissions in 2017, whereas the Assumed operation results were five times greater. These disparities may be attributed to the assumptions and assessment conditions. When estimating the emissions using the GMB approach, the technologies considered differed. The power sources included in the average European grid mix used for GMB operation varied from those of the Norman grid. The EFs for the use phase evaluation were thus altered and so were the saved emissions. As for the assessment of

the use phase using the Assumed technique, the assumption that the power generated by the ESS substituted generation from thermal sources with 40% efficiency may constitute an exaggeration. This statement considered a single source to feed the ESS (i.e. thermal power) and did not actually take into consideration charge/discharge or the temporal variability of generation from RES, among other factors. Therefore, the actual operating conditions and constraints were not adequately accounted for, and the misinformed scenario engendered misleading results. Furthermore, optimizing the power generation patterns resulted in a grid mix dependent primarily on nuclear power with reduced reliance on fossil fuels. The BESS was therefore mostly charged from a source with a low CO_2 EF, making the saved emissions from its optimized operation lower than those computed using the assumed operation approach. The impact results from the use phase confirm the findings in (Oliveira et al., 2015), which emphasize the fact that ESS performance is linked to the electricity feedstocks used in its operation. Therefore, to effectively add the ESS to the grids, the sources it is meant to substitute should have high EFs to further highlight the emissions saved with its introduction in the system.

5.4.4.2 LCA of ESS

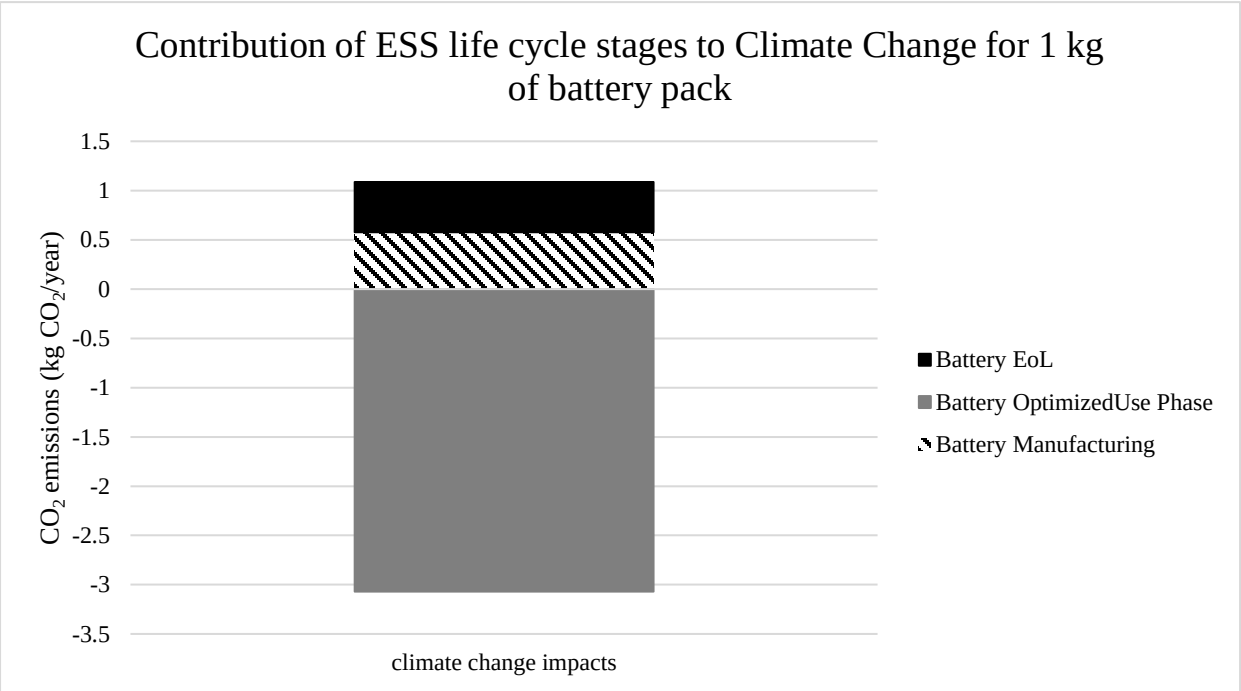

Figure 5.7 Comparison of the contributions of LCA stages to the Climate Change impact category for 1 kg of battery pack

Figure 5.7. illustrates the annual environmental impact contribution of each ESS life cycle stage to climate change for one kg of battery pack in 2017. The saved emissions from the use phase of the batteries outweigh the CO_2 generated during their manufacturing and EoL. Hence, from a holistic perspective ensured by the LCA of the batteries, they are recommended for the application at the grid level. This difference in CO_2 generated between the steps is attributed to several reasons: 1- the power sources substituted by the ESS (mainly fossil fuels), 2- the optimized grid operation which allowed the optimal operation of the BESS at periods where it was the most impactful and 3- the technological advancement in the manufacturing processes of this type of batteries, reducing the emissions from this stage along with the more detailed inventory used in the calculation. These results prove that the Li-ion technology is very competitive in the storage systems market from an environmental perspective and it is thus recommended to improve not only the RESs penetration but the entire grid footprint.

The emissions generated during the manufacturing of the BESSs were due to the raw materials extraction and processing procedures adopted. In what concerns the EoL of the batteries, the incineration process is to be reconsidered. There is a lack of accurate data regarding this life cycle step of the grid batteries. Currently, only 5% of the Lithium-ion batteries in the market are being recycled and the collection facilities are limited. The rest is either incinerated or landfilled which justifies our assumption. However, we recommend the use of more accurate information once available.

The assessment results are tied to the total ESS capacity considered and the available grid technologies. That is, different ESS capacity and/or grid technologies might enhance or worsen the footprint. Also, to better reflect the emissions from the battery manufacturing process, the inventory should be based on industrial data for stationary applications rather than the adaptation of electric vehicle batteries. However, in this study, the main focus was the use phase modelling of ESS, which was not affected by the type of battery (automotive or stationary) and reliance on automotive batteries for the assessment was therefore considered reasonable.

5.4.5 Added value and applicability of the new method

The new method facilitated the estimation of avoided emissions from the optimal grid operation deploying an ESS. It enabled enhanced use phase modelling of the batteries through the representation of their time-variant operation. These factual operation patterns lead to an accurate interpretation of the power sources that charge the storage system and their timing. Additionally, the consequences of the batteries addition on the remaining power sources generation were more clearly identified. Therefore, instead of setting up fixed scenarios or doing extrapolations, the evaluation of the environmental impacts of the entire life cycle of the storage system was improved.

In the scenario considered, no maintenance was performed, no sudden change in demand occurred and no shutdown of power plants happened. So, even though a best-case scenario was assessed retrospectively in this paper, the new technique provided an idea of the potential consequences of the optimal operation of batteries. The optimization step improved the management of the power supply, lowering the cost of the operation and GHG emissions whenever batteries were added to the system. Therefore, the interpretation of the technologies impacted by the ESS operation and the decision-making process regarding prospective ESS deployment in power grids were improved.

The LCA of the BESS served as a holistic overview of the awaited benefits from its deployment in Normandy. The results emphasized the saved emissions from the batteries operation which outweighed both its manufacturing and EoL resulting CO_2. Hence, batteries were so competitive in the storage systems market especially from an environmental perspective and more precisely in the geographical location considered.

In this paper, the specificities of the power plants were relevant to Normandy and based on local sources. Hence, it is important not to extrapolate the results of this study outside the Norman context and rather adapt the methodology to each specific case study.

5.4.6 Limitations of the developed approach and further research

Aside from its benefits, there are still a number of limitations to the proposed methodology. First, due to the significant share of the electricity trade in France and Europe as a whole, the consideration of imports and exports would be of great interest. The addition of ESS to a grid could impact the imports/exports and the power generation in its neighboring regions. Thus, it could remarkably change the assessment results. However, in this paper, the region considered was a net exporter so the exports were taken into account as loads. Second, the main idea of this paper was to present a new LCA approach and demonstrate its usefulness. Hence, relying on generic data for the grid assessment and adapting data from electric vehicle batteries for the ESS were acceptable. However, when there are no confidentiality issues, specific data for power plants and industrial data for stationary BESSs for grid-scale applications are preferred to enhance the accuracy of the LCA results. Third, the scenario assessed was representative of best-case conditions. Testing other scenarios, such as the worst-case scenario, where prices and demands change drastically and system faults occur along with other energy storage technologies, would be useful. Such scenarios will allow a more holistic evaluation before beginning the decision-making process regarding the deployment of ESS in power grids. Moreover, rather than applying the method retrospectively, it could be of great interest to perform an O-C-LCA in real-time and test it prospectively. This facilitates the tracking of changes in generation patterns as compared to the forecasted generation and the planning of the ESS operation to reduce costs. Lastly, the assessment was modeled using

a simplified optimization approach for environmental assessment purposes. Grid operators who require more complex models must adapt their optimization algorithms accordingly.

5.5 Conclusion

This paper presents an optimized consequential life cycle assessment methodology applied in a time-variant context. The method fills the gap in the literature recommending a new tool to investigate the dynamic operation of ESSs. The A-LCA made it possible to evaluate the life cycle impacts of the ESS, including its use phase, whereas the C-LCA facilitated the assessment of the resulting changes in power grids and emphasized the ensuing benefits of its deployment. Li-ion batteries were virtually deployed in the power grid of Normandy (France) to demonstrate the new technique. The results highlighted the increased accuracy of the environmental impact assessment of the electric grid while considering its changes. The optimized power generation and the time-dependent evaluation lead to near-real ESS operation patterns and enabled an enhanced computation of the saved emissions from its addition. The optimal operation of ESS resulted in an overall decrease of 53% in the annual CO_2 emissions of the grid electricity production. When evaluating the entire life cycle of the BESS, the emission savings from its operation outweighed the impacts of its manufacturing and EoL. This evaluation emphasizes the environmental competitiveness of this technology and its awaited benefits. From an economic perspective, our results suggested that the addition of the ESS was beneficial at the grid operation level as well. Under the considered conditions of the study, the optimal operation of the grid deploying batteries have led to a 28% reduction in the marginal costs of generation. However, to assess the economic benefits for the grid operators, the entire life cycle costs of the batteries need to be evaluated. Despite the representation of a theoretical best-case scenario, the O-C-LCA is regarded as a convenient tool to support the power sector decision-makers and, more specifically, provide a clearer assessment of the consequences of ESS deployment on the power grids operation. This methodology may also be adapted and applied to other temporally-variable systems and is suitable for testing in real-time operations.

Acknowledgment

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CHAPTER 6 ARTICLE 2: EVALUATING THE AVOIDED ENVIRONMENTAL IMPACTS FROM THE OPERATION OF ENERGY STORAGE SYSTEMS

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Abstract

Negative impacts on human health and ecosystem quality need to be considered in addition to climate change to ensure the sustainability of the energy sector. To date, accounting for the cost of these damages (i.e. external cost) in the modelling and assessment of grids is still limited, and its effect on the operation of energy storage systems (ESS) is lacking. This paper proposes a new method to evaluate and compare the avoided environmental impacts from the operation of lithium-ion batteries (as an ESS) when the external costs of electricity generation are considered. The climate change, human health, and ecosystem quality impacts were incorporated into the optimization of the power grid via monetization followed by the evaluation of the generation patterns by means of a life cycle assessment. Results showed that the optimization of electricity production is highly influenced by externalities. The optimized grid deploying an ESS decreased GHG emissions by 40% and saved around 22.5% in the total cost of generation compared to the base case (unoptimized grid). When the optimization function focused on minimizing the climate change impacts only, the ESS operation prevented more GHG emissions but saved 4 and 3% less ecosystem quality and human health impacts respectively. This method improved the modelling of

energy storage systems use phase and enhanced their potential environmental impact assessment. Internalizing the externalities in the evaluation of energy systems allows policy-makers to take appropriate measures to avoid problem shifting and increase the benefits to society.

Keywords

Life cycle assessment, Optimization, External costs, Impact categories, Power grids, Energy storage.

Highlights

- Internalizing the externalities enhances the grids environmental profiles
- Including external costs helps avoid problem shifting in electricity generation
- Energy Storage Systems avoid more impact when externalities are internalized

6.1 Introduction

The European Commission defines the external cost of electricity, or externalities, as the price of the environmental damage caused by the electricity generation process that is not accounted for nor compensated by the producers (http://www.externe.info/externe_2006/externpr.pdf). To ensure the sustainability of the energy sector and support informed decision-making for climate mitigation strategies (Prakash & Bhat, 2009; Spalding-Fecher & Matibe, 2003), there is a need to go beyond the greenhouse gas (GHG) emissions and incorporate measures for protection against human health (HH) and ecosystem quality (EQ) damages (Fortier, Teron, Reames, Munardy, & Sullivan, 2019). Accounting for externalities supports prospects for energy transition (Weldu, Yemane W., 2018) and can result in large quantifiable economic benefits (Weldu, Yemane W & Assefa, 2016) as highlighted in the U.S. Environmental Protection Agency (EPA) Clean Power Plan (U.S.EPA, 2015).

Previous assessments of electric grids have largely focused on climate change (CC) (Machol, Ben & Rizk, Sarah, 2013; Markandya & Wilkinson, 2007), with few studies evaluating the effect of internalized externalities on the operation of different power sources (Sakulniyomporn et al., 2011; Samadi, 2017; Streimikiene & Alisauskaite-Seskiene, 2014; Streimikiene et al., 2009; Weldu, Yemane W., 2018). Both the internalization of externalities and the incorporation of the life cycle

assessment (LCA) in the optimization of the grids were suggested to properly assess the damage to HH and EQ for energy system planning (Milutinović, Stefanović, Dassisti, Marković, & Vučković, 2014; Münster & Lund, 2009). Compared to other new technologies included in such planning, energy storage systems (ESS) are among the least assessed. The applied LCA methods either omit the evaluation of the ESS use phase or rely on assumptions and extrapolations to model this step while focusing on GHG emissions (Ahmadi et al., 2014; Hiremath et al., 2015; Oliveira et al., 2015; Sternberg & Bardow, 2015).

Since battery energy storage systems (BESS) are expected to play a vital role in the future grid (Guney & Tepe, 2017), it is crucial to understand how their operation would be impacted by the internalization of power generation externalities to better promote clean energy and create cost-effective and environment-friendly solutions (Munksgaard & Ramskov, 2002; Owen, 2004). Accounting for externalities when optimizing the electricity generation affects the environmental profiles of the grid and consequently alters the avoided impacts from the operation of ESS. In addition, change in batteries loading sources would impact the potential cost reductions from their operation.

To the best of our knowledge, a method capable of adequately reflecting how the operation of BESS is affected when the power generation accounts for externalities is still lacking. A study of this kind is expected to help better understanding the role of ESS in power grids and provide decision-makers with a clearer view of their anticipated environmental benefits. This manuscript proposes a new method to assess the use phase of ESS when the externalities of electricity generation are internalized with an aim to evaluate its potential environmental impact.

6.2 Material and methods

The Norman power grid (Normandy, France) was used as a case study since it includes diverse generation sources and its historical operation data is publicly available (RTE). In this study, Lithium-ion (Li-ion) batteries were chosen as energy storage systems due to their maturity and dominance of the grid-scale storage (Dunn et al., 2011; Hiremath et al., 2015; U.S.DOE, 2015).

The avoided environmental impacts from the ESS use phase were evaluated for three main scenarios:

i) “Base case” scenario to represent the historical grid.
ii) “Total cost optimization” scenario to represent the optimized grid operation in terms of generation and external costs.
iii) “GHG cost optimization” scenario to represent the optimized grid operation in terms of generation and CC impact cost only.

Grid data, monetized impacts, and ESS data were used to generate the optimized grid profile and estimate avoided impacts (Figure 6.1). Grid data were obtained from the French Transmission system operator (RTE) (RTE). The monetized impacts of electricity generation in 2018 (Table 6.1) were estimated by means of linear interpolation from the Cost Assessment of Sustainable Energy Systems project (CASES) database (Porchia & Bigano, 2008). The generation cost was referred to as *private cost* in the CASES database and the external costs included climate change (CC), human health (HH) and ecosystem quality (EQ)damage-related costs. Finally, the specifications of Li-ion battery ESS were based on (Elzein et al., 2018).

An optimized grid profile (Figure 6.1) was computed for each scenario using the algorithm of the optimized-consequential LCA (O-C-LCA) methodology described in (Elzein et al., 2018). The O-C-LCA has been proven appropriate for the evaluation of ESS operation, and therefore was used to assess its avoided impacts when externalities are internalized. The optimization algorithm of the O-C-LCA was modified to internalize the costs of impacts on HH and EQ in addition to minimizing GHG emission and generation costs.

The LCA methodology (ISO, 2006a, 2006b) was used to evaluate the potential environmental impacts of electricity generation from the various technologies in the Norman power grid and to estimate the avoided impacts from the ESS operation. For the assessment, OpenLCA software (version 1.7) (GreenDeLTa) and the ecoinvent database (version 3.4) ("Ecoinvent,") were used and IMPACT2002^{+} was chosen as a life cycle impact assessment method (Jolliet et al., 2003) (Table 6.2). In this manuscript, the focus was on the batteries use phase; further details on the LCA of the study and the environmental impacts of the remaining life cycle stages of the batteries are available in (Elzein et al., 2018).

Once the different electricity generation patterns were obtained, their environmental and economic profiles were analyzed and compared to the base case.

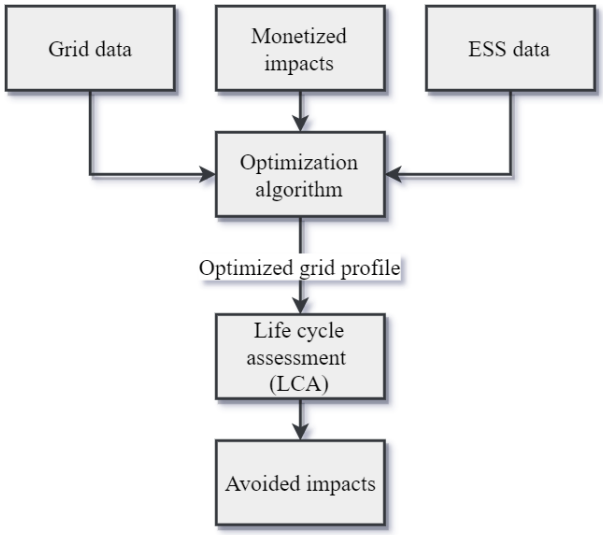

Figure 6.1 Methodological framework for the estimation of avoided impacts from ESS operation when externalities are internalized

Table 6.1 Detailed costs of the dispatchable sources in the 2018 Norman grid

Source	**Technology**	**Generation cost (€c/kWh)**	**CC impacts cost (€c/kWh)**	**External cost* (€c/kWh)**	**Total cost** (€c/kWh)**
Nuclear	Nuclear power plant	2.716	0.025	0.155	2.871
NG	Gas turbine	6.596	1.315	2.249	8.845
	Combined Cycle without CO_2 capture	4.626	0.845	1.442	6.068
	Combine Cycle CHP with backpressure turbine	4.278	0.894	1.533	5.811
	CHP with extraction condensing turbine without CO_2 capture	4.320	0.782	1.338	5.658

Oil	Heavy oil condensing power plant	7.066	0.438	2.877	9.943
	Light oil gas turbine	10.038	0.917	2.835	12.873
Coal	Hard coal condensing power plant	3.250	1.610	3.264	6.514

*External costs include the CC impacts costs

**Total cost is the sum of generation and external costs

Table 6.2: Detailed emission factors (EF) of the dispatchable sources in the 2018 Norman grid

Sources	**EF CC (tCO_2-eq/MWh)**	**EF HH (DALY/MWh)**	**EF EQ (PDF*m^2*yr/MWh)**
Nuclear	0.0120	59.3715	1.06E-04
NG	0.6193	12.5828	8.51E-05
Oil	0.9069	122.5573	8.88E-04
Coal	0.9597	443.5578	5.98E-04

*****CC: climate change, HH: human health, EQ: Ecosystem quality

6.3 Results and discussion

6.3.1 Cost comparison

The price of 1 kWh of electricity varies according to the different costs included in its estimation. The kWh price would be much higher when the costs of impacts on climate change, human health, and ecosystem quality are internalized in the cost function.

In the base case scenario, electricity was mainly generated from nuclear power and coal sources. This highlights the fact that the external costs of electricity production on human health (HH) and ecosystem quality (EQ) were not considered. Once these costs were added, the ranking of preferred

technology for generation changed and led to the discrepancy in generation patterns and results between the base case and the two optimized scenarios (i.e. Total and GHG cost optimization).

In the case of the Norman grid, nuclear power is the most advantageous generation source in terms of both private and external costs due to its mature nature, cheap cost of production, and low carbon intensity (Table 6.1 and Table 6.2). Coal was ranked second cheapest electricity generation source (Table 6.1) but was found to be the most damaging in terms of all three impact categories considered (Table 6.2). The external cost of coal was ~ 21-fold higher compared to nuclear power (Table 6.1). In addition to its significant GHG emissions, the operation of coal power plants deteriorates EQ and damages human health. Aware of the adverse impacts of electricity generation from coal, the French government aims to completely decommission operating coal power plants by 2022 (WNN, November 2018).

Natural gas (NG) ranked second-best option to generate electricity due to its relatively low externalities (Table 6.2) despite its high private cost compared to coal. It is evident that the damages caused by coal are worse than NG which explains why its externalities are double. As for oil power sources, improvements are needed to lower their generation costs and reduce their impacts.

6.3.2 Comparison with the base case

The GHG emissions in the 2018 base case were 40% higher compared to the total cost optimization scenario (Figure 6.2) over the entire year of the study. This difference is explained by the optimization of generation patterns, and the deployment of an ESS into the grid. The batteries contributed to the reduction in emissions by partially substituting fossil fuels during peak hours. Nuclear power was favored in certain periods and contributed to further lowering the climate change impact of the grid due to its low GHG emission compared to other sources (i.e. fossil fuels). The lower GHG emissions from the optimized grid (Figure 6.2) were also reflected in terms of potential cost reduction.

The optimized generation saved ~3 megatons of CO_2-eq (Figure 6.2) and would have potentially reduced the Norman grid operation cost by 131 million euro (22.5% reduction in cost) assuming the 2018 French government price of 44.6 Euro/ton of CO_2-eq. Under these optimized operating

parameters, cost-saving would allow government and grid-operators to invest in low-carbon intensity energy generation options.

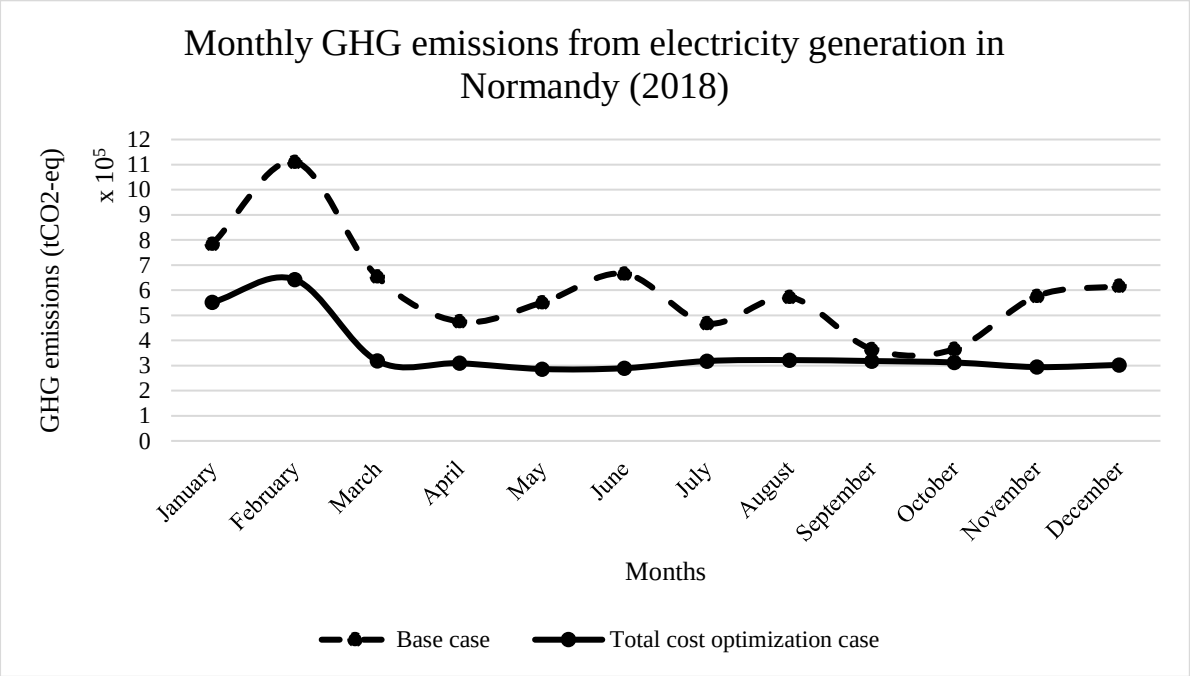

Figure 6.2 Variation in the 2018 monthly GHG emissions between the base case and the total cost optimization scenarios.

6.3.3 Effect of internalized externalities on ESS operation

The external costs of human health and ecosystem quality are often overlooked during the optimization and evaluation of power grids (ExternE; Samadi, 2017; Weldu, Yemane W., 2018). The avoided impacts and potential cost reduction from both scenarios were evaluated and compared (Table 6.3) to highlight the added value of the developed approach and to compare our data with the literature.

Table 6.3 Total annual impact and potential cost reduction on the three impact categories according to the different optimization objectives

Scenario	Annual voided impacts			Potential annual cost reduction			Total potential annual cost reduction (€)
	CC (tCO_2-eq)	EQ ($PDF.m^2.yr$)	HH (DALY)	CC (€)	EQ (€)	HH (€)	
GHG cost optimization	6 389	12 460 146	21.620	105 065	44 706	261 826	**411 597**
Total cost optimization	6 000	12 949 561	22.340	97 796	52 565	272 925	**423 286**
Difference	**6%**	**4%**	**3%**	**7%**	**15%**	**4%**	**3%**

6.3.3.1 Avoided impacts

As expected, the ESS operation in the GHG cost optimization scenario was more advantageous with respect to climate change. This objective focused on reducing the CO_2-eq emissions while accounting for the costs of generation and ignoring the remaining impact categories (i.e. HH and EQ). In addition to lowering the generation for the main GHG emitting sources, the Li-ion batteries substituted the remaining fossil fuel sources during peak demand periods so their operation in the GHG focused case resulted in a 6% additional emission savings compared to the other scenario.

In terms of EQ and HH, the operation of the storage system in the total cost optimization avoided 4 and 3% more impacts respectively compared to the GHG optimization scenario. In this case, the optimization function compromised the various costs in order to find the best generation patterns in terms of all three impact categories. Decision-makers, therefore, need to account for CC, EQ, and HH simultaneously to improve their grids profiles while avoiding problem shifting between the categories.

In the optimization scenarios evaluated (i.e. Total and GHG cost optimizations), nuclear power was favored over the remaining sources. Despite the minimal impact on the three categories, uranium mining affects the resource depletion category remarkably (Srivastava, Pathak, & Perween, 2020). Both optimization scenarios did not account for the resource depletion impacts and resulted in a similar environmental profile. Therefore, it would be of interest to optimize the grid operation in terms of the resource depletion category in order to have a more holistic evaluation and to avoid problem shifting when proposing alternative energy solutions.

6.3.3.2 Potential cost reduction

The avoided impacts translated into potential cost reduction as well. The addition of ESS and its operation in the GHG cost optimization scenario led to an additional 7% potential CC cost reduction. Replacing more CO_2 emitting sources prevented their impact and thus reduced their corresponding impact cost. However, energy sources with less GHG emissions are not always the best electricity generation options in terms of resulting damages to health and the ecosystem (Table 6.2). This is why the compromise between CC, HH, and EQ lacking in this scenario resulted in fewer savings in the two remaining impact categories. The total cost optimization scenario saved 15 and 4% more money at the EQ and HH levels respectively compared to the GHG optimization scenario.

In addition to EQ and HH, the French decision to shut down coal power plants (WNN, November 2018) would definitely result in impact savings at the resource depletion level. It would, therefore, be of interest to investigate the grid profile once the decision is enforced.

However, the potential cost reduction from the ESS operation is expected to decrease when the Norman grid switches to low-carbon intensity sources for electricity generation. That said, batteries would not serve peak demand in the future 100% renewable grids, substituting fossil fuels and avoiding their environmental impacts. Instead, batteries will be mainly deployed to ensure the stability of the grid operation when intermittent sources, such as wind and solar power, are in operation. The change of ESS role will, therefore, affect the anticipated monetary savings of the grid-operators.

It is important to mention that the estimation of avoided impacts and potential cost reduction is highly dependent on the monetization method used. The reliance of CC, HH and EQ related

damages on different monetary values influences the results and affects the decision-making process. It would be of interest to look at different monetization methods to evaluate their effect on the optimized electricity generation patterns and the consequent impacts and potential cost reduction from ESS operation.

6.3.4 Advantages and limitations

Advantages

Internalizing externalities in the O-C-LCA further enriched the O-C-LCA methodology allowing a holistic evaluation of time-dependent systems such as power grids. The new method enabled grid-operators to better model and understand the consequences of changes within their systems. The method outlines the compromise between the CC, HH and EQ impact costs and alteration of the electricity generation patterns and consequently their environmental profiles. Additionally, this method facilitates the assessment of the ESS operation when the external costs of electricity generation are considered. The temporally-variable operation of the ESS, the consequences of including grid externalities on the optimized operation of batteries, their avoided impacts, and potential cost reduction have been better represented.

Limitations

Despite its advantages, the developed method has several limitations. Dealing with fixed costs of generation is a simplifying assumption. This cost, especially for fossil fuels, is subject to change following different factors (political, geographical, etc.) and this assumption might only approximate reality. In addition, the resource depletion impacts were ignored, and it would be of interest to consider the impacts on this category since France relies mainly on nuclear power and is willing to invest in this technology in the future.

6.4 Conclusion

This manuscript presents a new method to evaluate the effect of internalizing the external costs of electricity generation on the operation of ESS. The cost of climate change, human health, and

ecosystem quality impacts were internalized in the O-C-LCA methodology and applied to the Norman power grid. The method enhanced the modelling and assessment of internalized externalities on the environmental profile of optimized power grids. It also improved the analysis of the impacts and avoided costs from the operation of batteries. Results showed that optimizing the grid operation in terms of the total cost can lead to 40% less GHG emissions than the 2018 base case and can save up to 131 million €. While the operation of ESS resulted in greater CC impacts and avoided costs when the grid was optimized in terms of GHG emissions alone, accounting for externalities improved its performance on the EQ and HH levels. The added value of the ESS was further highlighted when the three impact categories were compromised, and the potential cost reduction from grid optimized in terms of the total cost was higher. In sum, the O-C-LCA provided a clearer understanding of the ESS operation when externalities were included. It facilitated also the modeling and evaluation of changes to the power grids and improved their interpretation.

Acknowledgment

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CHAPTER 7 ARTICLE 3: ENVIRONMENTAL ASSESSMENT OF POWER GRIDS IN THE SHORT-TERM

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Abstract

Grid operators are under constant pressure to optimize their generation and adhere to energy and emission goals. The modelling of electricity generation and the evaluation of energy policies in prospective contexts need improvement. The dynamism of grids should be better represented, and their short-term environmental assessment must be enhanced. Mindful of these limitations, this study reports a novel method combining scenario analysis and life cycle assessment (LCA) in an optimization framework. The model considers the future grid specifications and environmental limitations to develop the potential 2023 power grid of Normandy in France. The optimization algorithm minimizes the cost of grid operation and the LCA is then used to evaluate its environmental impacts. Results show that the energy strategy enforcing the shutdown of coal power plants and the addition of renewable energy sources can lead up to 64% lower grid greenhouse gas emissions compared to 2018. Further 6% reduction in emissions is anticipated if the Flamanville 3 nuclear reactor begins operation. Results also suggested that the complete decommissioning of oil sources might ensure the best environmental performance of the 2023 grid. In terms of total operation costs, the different scenarios result in a comparable reduction of 19% vis-à-vis the 2018 grid. In sum, the developed method described here is convenient for the evaluation of energy targets despite the uncertainties associated with future operations. It enriches the environmental

assessments of energy systems in the short-term and may serve as a reliable and practical tool in supporting decision-making.

Keywords

Prospective analysis, life cycle assessment, future grid, optimization, energy targets.

Highlights

- Combining LCA, scenario analysis and optimization to evaluate future grids.
- The environmental profile of the 2023 Norman grid is analyzed under grid constraints.
- 2023 Norman grid operations can reduce its CO_2-eq emissions by 64% compared to 2018.
- Short-term grid assessment is important for energy and emission targets evaluation.

7.1 Introduction

The energy sector is evolving worldwide to address climate change (Khan, I., 2018). Policies and legislation are being introduced to reduce greenhouse gas (GHG) emissions (Gómez et al., 2016; Ouedraogo, 2017), set short and long term energy goals (Herman, 2019; Press, 2018; Rankin, 2019; Sauer & Mathiesen, 2019), promote a higher penetration of renewable energy sources (RES) (IEA, 2018; REN21, 2019) and reduce the reliance on conventional power plants (Martín-Gamboa et al., 2019). Future electricity generation systems and their environmental impacts must be assessed to evaluate compliance with current climate mitigation goals and draft future policies (Padey et al., 2013).

Life cycle assessment (LCA) is a holistic approach that estimates the environmental impacts of products and services over their entire life cycle (ISO, 2006a, 2006b). It is a convenient tool to evaluate environmental performances and assess energy systems (Blanc & Beloin-Saint-Pierre, 2013; Pehnt, 2006; Sørensen, 2011). However, modelling the life cycle of future electricity generation is a complex task necessitating a tremendous amount of data (Blanc & Beloin-Saint-Pierre, 2013). As a consequence, different tools such as energy system models (ESMs) are often combined with LCA to improve robustness and to account for different energy-related problems (García-Gusano & Iribarren, 2018; García-Gusano, Iribarren, & Dufour, 2018; García-Gusano, Istrate, et al., 2018; Kondili, 2010; Navas-Anguita et al., 2018).

Energy system models are exploratory mathematical models used to project energy demand and supply of a region/country (Hall & Buckley, 2016) in addition to identifying and solving energy issues (Kondili, 2010). They facilitate the development of optimized operation scenarios while considering factors such as energy prices, economic activities, future technologies, energy targets, market dynamics and policies (Herbst et al., 2012). Methods combining LCA and ESMs have been applied to assess the environmental profiles of future power grids in various geographical locations (Astudillo et al., 2017; Dandres, T. et al., 2012; Dandres, T. et al., 2016; García-Gusano, Garraín, et al., 2017; García-Gusano et al., 2016; Krook-Riekkola et al., 2013; Maïzi & Assoumou, 2014; Vandepaer et al., 2018). However, the high level of computational complexity (Giannakidis, Labriet, Ó Gallachóir, & Tosato, 2015), inability to model short-term prospects (García-Gusano, Garraín, et al., 2017; Loulou, Richard et al., 2005), and the long runtime limit the use of these models and render them, in certain cases, impractical for policymakers (Howells et al., 2011). In addition, the real environmental profile of the electricity generation can be inaccurately computed due to the intra-annual time splits. Hence, the LCA/ESMs methods fall short in fulfilling policymakers' requirement for a legislation assessment method of reduced-complexity (Lacirignola et al., 2014; Padey et al., 2012). An easy-to-use multipronged tool that is capable of taking into account the sustainability constraints of the energy systems while also being applicable to short-term policy evaluation is needed (Padey et al., 2013; Raugei & Leccisi, 2016).

To fill the gap, this manuscript outlines the development of a novel methodology that is simpler, less time-consuming, and more suitable for short-term environmental assessments compared to the LCA/ESMs methods. The new method was based on the optimized-consequential LCA (O-C-LCA) developed in (Elzein et al., 2018) and relies on soft-linking an environmental scenario analysis (ESA), an optimization algorithm, and LCA. The ESA step, which consists of building scenarios based on models and scientific literature was added to help develop different future grids (Alcamo, 2008a, 2008b). Once the scenarios were defined, the operation of the grids was modelled using the optimization algorithm and the environmental profiles were then evaluated using LCA. These methodologies were soft-linked to 1) capture the different viewpoints they offer, 2) improve prospective scenario modelling, 3) enhance short-term environmental impacts analysis of power grids, and 4) support decision-makers in the preliminary evaluation of the energy targets. To the best of our knowledge, a method combining these approaches has not been developed yet.

The manuscript is organized into five sections. Section 7.2 introduces the case study. The methodological steps and different scenarios and assumptions are explained in section 7.3. The results of the different cases and energy targets are presented and discussed in section 7.4. The advantages and limitations of the new method are also highlighted in section 4. The conclusion and the main findings are summarized in section 7.5 of the manuscript.

7.2 Case study: The power grid of Normandy (France)

The power grid of Normandy (France) was selected to demonstrate the applicability of the O-C-LCA (Elzein et al., 2018) in a prospective context due to the following reasons. First, the Norman grid can be considered representative of other grids in the world because it relies on both renewable and non-renewable power sources (RTE). Second, historical data along with installed capacities and specifications of the different power plants are publicly available (RTE). Moreover, the energy plan of the region detailing the projected installations over short and long-terms is also available to the public (Courtel, Houot, & Le Jannic, 2018). Finally, the country, as a whole, has been interested in lowering the environmental impacts of its energy sector through the development of a national low-carbon strategy (MTES) and the introduction of carbon taxes on coal, heavy fuel oil, and gas since 2014 (WorldBank).

7.3 Material and methods

7.3.1 Overview of the methodology

The developed methodological framework (**Figure 7.1**) was based on the modification of the optimized-consequential LCA (O-C-LCA) approach developed earlier (Elzein et al., 2018). The O-C-LCA is a two-step method that consists of an optimization step to model power grids and an LCA step to assess environmental impacts. The O-C-LCA was adapted to prospective studies through the addition of an Environmental Scenario Analysis (ESA) step to develop different future scenarios. The methodological steps are outlined in Figure 7.1 and summarized below:

1- First, the status quo of the 2018 Norman grid was analyzed. The environmental impacts of the historical grid operation were evaluated by means of an LCA. The historical grid serves as a basis for the comparison with the future grid to emphasize the change in the environmental impacts of electricity generation.

2- Next, an environmental scenario analysis (ESA) step was added to develop different scenarios. Future grid constraints according to the Norman energy plans were taken into consideration in the different scenarios. The O-C-LCA was then adapted by including future grid goals instead of defining a change to the system as described before (Elzein et al., 2018).

3- To prospectively model the grid, the targeted installed capacities, grid constraints, energy goals, and environmental regulations were implemented into the optimization algorithm. This algorithm minimizes the total cost of electricity production, including the costs of generation and GHG emissions. Taking the total electricity consumption and electricity generation from RESs as input generates the operation patterns of fossil fuels and nuclear technologies. The optimized 2023 Norman grid operation was therefore obtained on a 30-minutes basis with an overview of each technology share at every time slot. The optimization step is further detailed in section 7.3.4.

4- The various electricity generation profiles were evaluated using LCA and their potential environmental impacts were interpreted. The different operation patterns were finally compared with the 2018 grid and between each other to better understand how future changes might affect the environmental profile of the grid.

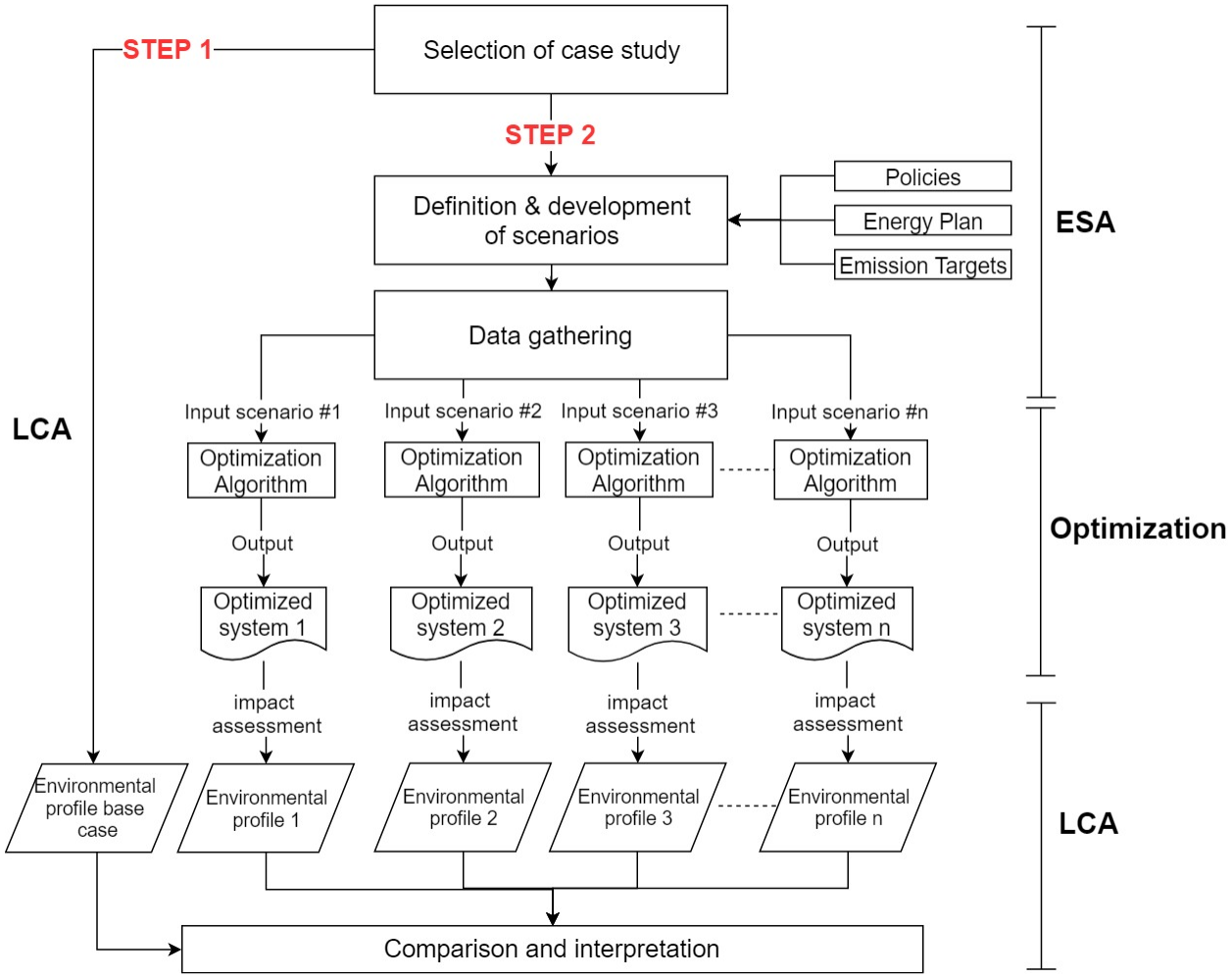

Figure 7.1 Methodological framework to model and evaluate the future energy system.

7.3.2 Evaluation context

Electricity consumption and RES operation in 2023 were first forecasted to develop future scenarios

7.3.2.1 Norman electricity consumption in 2023

The variation in the adjusted annual average electricity consumption in Normandy was negligible (1% change) between 2006 and 2018 (RTE; RTE) (Appendix C Table C.1). The stability of electric consumption throughout this period motivated the forecast of the 2023 electricity consumption using linear extrapolation. The regional historical data used to derive electricity consumption were

provided by the French Transmission system operator (RTE) on a 30 minutes basis (RTE). The following methodology was followed to forecast the 2023 Norman consumption:

1- The historical consumption at a given time slot (e.g. 9:00 a.m. to 9:30 a.m. of a given day) was retrieved for every year between 2013 and 2018.

2- The average consumption at the given 30-minutes time slot between 2013 and 2018 was calculated to obtain the average consumption value for the corresponding time slot in 2023.

3- The process was repeated for every time interval to build the consumption curve for the entire year.

The same outlined procedure was used to forecast trade since Normandy is a net electricity exporter (RTE). The total consumption considered for the optimization included local demand and exported electricity.

7.3.2.2 Norman RES generation in 2023

The Norman targets of RES installed capacities in 2020 and 2050 were retrieved from "*Le baromètre 2018 des énergies renouvelables électriques en France*" report (Courtel et al., 2018). Targets capacities for wind, solar, hydro and bio-energies in 2023 were calculated using linear interpolation and were found to be 3,827; 2,813; 100; and 251 megawatts (MW) respectively (Appendix C Table C.2). The climatological forecast approach recommended by the National Renewable Energy Laboratory (NREL) was used to estimate RES electricity generation profiles in 2023 (Tian & Chernyakhovskiy, 2016). The *climatological forecast* approach consists of averaging the accumulated weather statistics to make the forecast (UoI). The following methodology was followed to forecast the 2023 RES generation patterns:

1- Calculate the percentage of growth of the installed capacity of every RES between each historical year i and 2023.

$$\text{Growth percentage}_{\text{year i}} = \frac{Installed\ capacity_{2023}}{Installed\ capacity_{historical\ year\ i}}$$

2- Multiply the historical generation of every RES in the year i by its corresponding growth percentage.

2023 Preliminary generation $_{\text{technology x}}$ = Growth percentage $_{\text{year i}}$ × Historical generation $_{\text{year i}}$

3- Obtain a forecast of the 2023 generation patterns for the RES based on year i.

4- Repeat the procedure for all historical years.

5- Calculate the average generation for each technology at every 30 minutes in the different 2023 grids to obtain the patterns considered in our study.

$$\text{Final 2023 generation} = \frac{\Sigma 2023\ preleminary\ generation}{6}$$

where 6 in the denominator is the number of historical years.

To better understand these calculations, an example of wind power is provided in Table 7.1. The historical generation at 1:00 a.m. on the 1st of January of each year was considered to calculate the generation from wind at 1:00 a.m. in 2023. The 2023 projected wind installed capacity is 3827 MW.

Table 7.1 Historical data for wind generation at 1 a.m. on January 1st

	2013	**2014**	**2015**	**2016**	**2017**	**2018**
Installed capacity (MW)	472	520	567	643	726	767
% of growth	811%	736%	675%	595%	527%	499%
Historical generation (MWh)	190	285	141	118	66	609
2023 preliminary generation (MWh)	1540.9	2097.6	951.75	702.1	347.82	3038.91
Final 2023 generation (MWh)	1446.51					

7.3.3 Scenarios definition and modelling

In this study, the operation of the 2018 Norman grid was compared with different grid operations in 2023 (Table 7.2). The default 2023 grid was developed using the **regional** energy goals whereas the 2023 **national** scenario was built following the French energy targets defined in the multiannual energy program and national low-carbon strategy (*Décret n° 2016-1442 du 27 octobre 2016 relatif à la programmation pluriannuelle de l'énergie* 2016; MTES).

Table 7.2 Difference in installed capacities between the historical and future Norman grids.

Source	Installed capacities (MW)		
	2018	**2023**	**2023**
	Historical scenario	**Default scenario**	**National scenario**
Coal	580	0	580
Oil	127.8	35.8	127.8
Natural Gas	510.2	510.2	510.2
Nuclear	10 640	10 640	10 640
Wind	767	3 827	1 636
Solar	131	2 813	501
Hydro	49.6	100	41
Bioenergy	114	251	227.3

7.3.3.1 Historical grid

The historical grid operation in 2018 was evaluated to understand the status quo of the Norman power system and the expected changes. Between 2018 and 2023, the investments in RESs increase their share of total installed capacities from 8 to 38%, whereas the decommissioning of several

fossil fuel power plants reduces their corresponding share from 9 to 3%. These major changes to the structure directly affect the environmental profile of the grid.

7.3.3.2 Regional scenarios

Three other regional scenarios based on a similar grid structure with several modifications were modelled, evaluated and compared to the default 2023 scenario (Scenario 1, Table 7.3). The assumptions adopted for scenarios 1 through 4 are summarized in Table 7.3 and further details about each case are provided afterward. The same electricity consumption, RES operation patterns and regional energy goals (Courtel et al., 2018; METS, 2016; WNN, November 2018) were applied to all four regional scenarios.

Table 7.3 Assumptions of the default 2023 and various regional scenarios.

Assumptions	**Scenario 1** **Default scenario**	**Scenario 2** **Zero-oil scenario**	**Scenario 3** **ESS scenario**	**Scenario 4** **Increased nuclear scenario**
Common assumptions	• Shutdown of coal power plants • Decommission of vapor cogeneration and piston motor oil technologies • Constant installed capacity of natural gas (NG) power plants • Installed capacity of RES increased • Price of CO_2-eq considered: 62.6 €/tCO_2-eq*			

Different assumptions	• Installed capacity of oil power plants reduced • Constant installed capacity of nuclear power plants	• Shutdown of oil power plants • Constant installed capacity of nuclear power plants	• Installed capacity of oil power plants reduced • 700 MW Li-ion batteries added • Constant installed capacity of nuclear power plants	• Installed capacity of oil power plants reduced • Installed capacity of nuclear power plants increased to 12 290 MW

* based on the national low-carbon strategy (MTES)

The zero-oil scenario, or scenario 2 (Table 7.3), was modelled and analyzed to understand how the complete decommissioning of oil sources would affect the grid operation, electricity generation shares, and environmental profile.

The ESS scenario, or scenario 3 (Table 7.3), highlighted the impact of energy storage. The O-C-LCA methodology has been proven useful in evaluating the impact of energy storage systems (ESS) on power grids (Elzein et al., 2018). The French government is currently investing in energy storage technologies (Clercq, 2018), and it is of interest to evaluate how the addition of batteries could affect the grid's GHG emissions. Therefore, the effect of deploying lithium-ion batteries in this scenario in the 2023 Norman grid was assessed.

The increased nuclear scenario, or scenario 4 (Table 7.3), emphasized the role of nuclear power sources in the region. The new pressurized water reactor, Flamanville 3, was assumed operational in 2023 following multiple delays and its rescheduling to the second quarter of 2020 (EDF, 2019; PowerTechnology, 2019).

7.3.3.3 National scenario

In scenario 5, the 2023 Norman grid was modelled according to the French **national** goals (*Décret n° 2016-1442 du 27 octobre 2016 relatif à la programmation pluriannuelle de l'énergie* 2016; MTES).

Operational technologies such as combustion turbine, piston motor, and vapor cogeneration in 2023 were assumed to be similar to 2018. For the RES, the installed capacities were determined based on the mean values of the upper and lower installed capacities for the year 2023 defined in the national low-carbon strategy (MTES).

The first step in the evaluation of the 2023 national scenario consisted of validating the achievement of the national goals followed by its comparison with the default 2023 scenario. First, we validated whether energy consumption and generation from coal, oil, and natural gas were reduced by 11.45, 33.64, 21.27, and 14.36% respectively in comparison to the annual average values of 2013. In addition, we validated that electricity generation from nuclear sources exceeded 55.4% of the average annual consumption. Next, the grid structure and environmental performance of the electricity generation pattern in the 2023 national scenario were compared to the 2023 default scenario. The comparison of national and regional targets highlights the significance of region tailored goals and emphasizes the importance of their update. It also helps position the Normandy region at the national level.

7.3.4 Optimization

The 2023 electric system technical specifications were implemented into the optimization algorithm to model the future grid operation. For this step, we relied on *"fmincon"*, a function built-in MATLAB to find a minimum of a constrained nonlinear multivariable optimization (MathWorks). The limitations of power balance were defined, and the ramping constraints of fossil fuels and nuclear sources were determined. The electricity generation constraints were then defined: all demand must be met by the local sources and the technical features of the conventional sources must be respected. For the costs of generation, they were assigned to each source according to the projected prices of the French government (METS, 2016). Once run, the algorithm satisfies the demand with the electricity produced by the RES and the remaining load is then met by

conventional sources. Further details about the grid constraints and costs considered are available in Appendix C while the optimization equations are included in Appendix D.

To model the various 2023 scenarios, we repeated the same procedure after modifying the algorithm and adjusting the operation constraints according to the scenario under evaluation.

7.3.5 Scenario analysis

7.3.5.1 Life cycle assessment

The LCA of the power generation technologies included in the Norman grid was carried out using OpenLCA (version 1.7.0) (GreenDeLTa). The inventories were based on the ecoinvent database (version 3.4) ("Ecoinvent,") and the damages were evaluated using the IMPACT 2002^{+} method (Jolliet et al., 2003). The life cycle phases considered in the analysis included the construction, production, and transportation of electricity. However, the impacts attributed to its final use, the recycling processes and end-of-life were excluded. Supplementary Information A presents the list of available technologies in the Norman grid and their corresponding ecoinvent processes. The functional unit of the study was "*Satisfy consumer demand for electricity at every 30 minutes in Normandy in 2023*".

The study evaluated the environmental profiles of the five 2023 scenarios and compared their monthly climate change impacts.

7.3.5.2 Scenario comparison

It is important to evaluate the power grid at endpoint levels other than climate change. To avoid problem shifting and explore the implications of changing the grid structure, the future grid operation for the remaining impact categories was assessed, namely human health (HH), ecosystem quality (EQ) and resource depletion (R). The total annual impact on these categories from the electricity generation in the four regional scenarios (Table 7.3) was calculated and compared.

Moreover, the assumptions of each scenario alter the generation shares of the non-renewable sources and vary the cost of operation. To highlight these changes, we compared the total cost of operation including the annual costs of generation and GHG emissions between the developed scenarios and the 2018 Norman grid.

7.4 Results and discussions

7.4.1 Comparison with the historical grid

The 2018 and default 2023 Norman grid were compared since the first step of the methodology consisted of understanding the *status quo* of the system.

7.4.1.1 Installed capacities and generation shares

The difference in the grid structure between 2018 and 2023 in terms of various power sources underscores the changes the Norman grid is expected to undergo (Table 7.2). Between 2018 and 2023, the investments in RESs increase their share of total installed capacities from 8 to 38%, whereas the decommissioning of several fossil fuel power plants reduces their corresponding share from 9 to 3%. These changes in the installed capacities of the different sources alter their shares from generation. (Table 7.4).

Table 7.4 Percentage of the shares of different sources in total electricity generated in 2018 and 2023 in the Norman grid.

Category	**Source**	**% of share from total annual electricity generation**	
		2018	**2023 (scenario 1)**
Fossil fuels	Oil	0.55	0.20
	Coal	2.48	0
	Natural Gas	2.18	0.79
Nuclear	Nuclear	91.43	82.33
Renewable energy sources	Wind	2.24	10.77
	Solar	0.24	4.01
	Hydro	0.19	0.41
	Bioenergy	0.69	1.48

Compared to the historical grid, electricity production from fossil fuels is anticipated to decrease by ~ 5-fold in 2023 due to the shutdown of the coal power plant and decommissioning of vapor cogeneration and piston motor oil technologies. In the default 2023 scenario, natural gas and combustion turbine oil plants are the only operational fossil fuel sources. As for nuclear power, its share from electricity production may be reduced approximately from 91.43% in 2018 to an expected 82.33 % in 2023. The increased renewables installation is a major reason for the decrease in the grid reliance on nuclear sources. The addition of RES, mostly wind and solar, increases their share from total generation by ~ 5-fold, from 3.37% in 2018 to an expected 16.66% in 2023. Therefore, the new grid structure that is less dependent on nuclear sources and barely relies on fossil fuels aligns with the transition plan toward greener energy systems.

7.4.1.2 Monthly average emissions

The change in the grid structure is also reflected in the electricity generation patterns and their corresponding emission profiles (Figure 7.2).

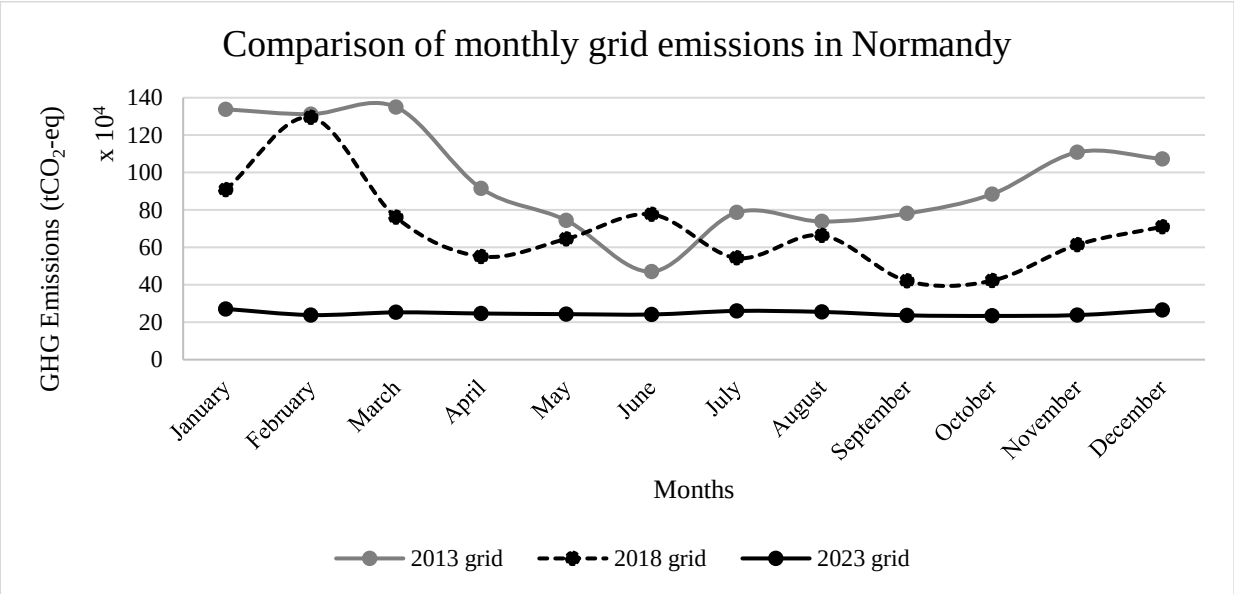

Figure 7.2 Comparison of the monthly CO_2-eq emissions from three Norman grids: 2013, 2018 and 2023 (Scenario 1).

The overall emissions of the 2013 grid are greater than those of the 2018 and 2023 grids due to the larger share of operational fossil fuels and limited deployment of RESs.

The overall GHG emissions in 2023 are expected to decrease to one fourth (1/4) of the annual emissions levels of 2013. This anticipated reduction is attributed to the significant contribution of wind and solar power to electricity production, the shutdown of coal power plants and the decommissioning of most oil sources. The burning of fossil fuels is an important source of GHG emissions and, in 2013, resulted in ~ 9.5 megatons of CO_2-eq (representing 83% of total emissions) (RTE).

The annual GHG emissions decreased by 35% between 2013 and 2018 due to the addition of RES. The installed capacity of RESs increased from 715 MW in 2013 to 1, 020 MW in 2018. Several fossil fuel sources were shut down, reducing their installed capacity from 1 477 MW in 2013 to 1 218 MW in 2018. The high discrepancy is observed between the curves at a monthly level (Figure 7.2) which highlights the importance of evaluating power grids over shorter periods to better represent the dynamism of operation and accurately identify periods of highest emissions.

If all the planned installations of RESs take place between 2018 and 2023, the GHG emissions from the optimized grid operation could decrease by 64%. The complete decommissioning of coal power plants, along with major investments in wind and solar power, would play a key role in inducing the change.

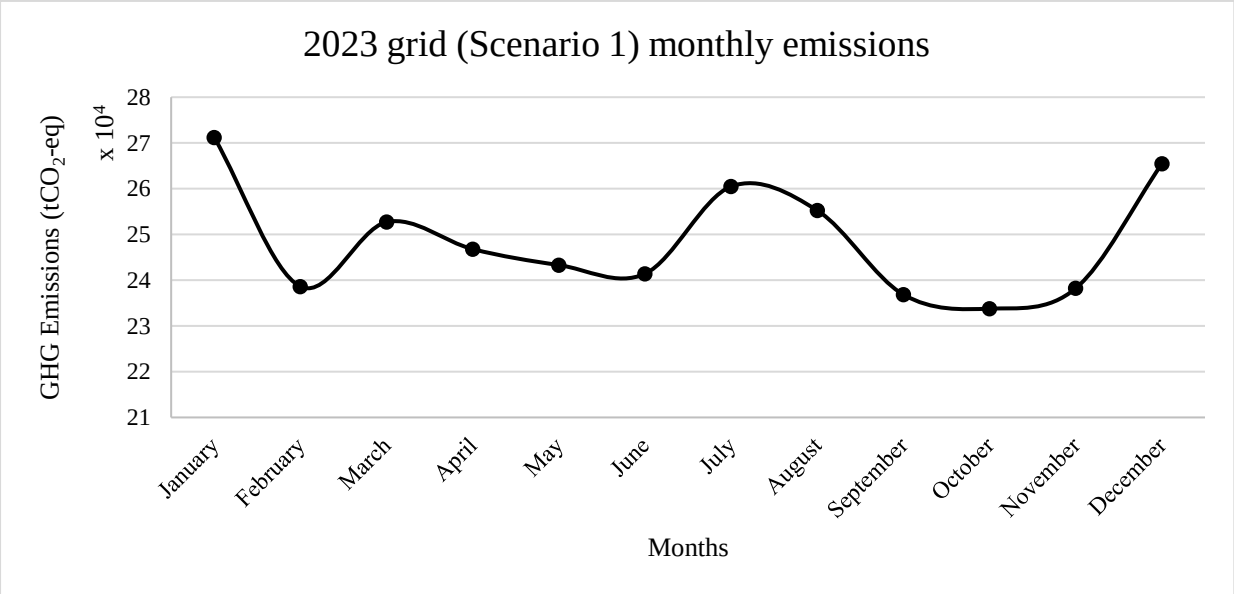

Figure 7.3 Expected monthly CO_2-eq emissions or the 2023 grid (Scenario 1). The y-axis does not start at 0 for visualization purposes.

In Figure 7.2, the expected monthly emissions of the 2023 grid appeared constant compared to the 2013 and 2018 grids due to scale. However, the 2023 monthly emissions are expected to vary with the seasons although in a different order of magnitude. To better understand the monthly variations, Figure 7.3 zooms in on the total monthly CO_2-eq emissions. Peak demand is anticipated in January 2023, when emissions are at their highest. Additionally, summer 2023 (mainly July and August) is expected to be responsible for a bigger share of the monthly emissions as compared to other seasons. It is anticipated that this increase in emissions will be owed to weather conditions. Hence, grid operators are requested to take the necessary measures to satisfy the peak demand during these periods without deteriorating the environmental profile of the grid operation.

7.4.2 Scenario comparison

7.4.2.1 Analysis of regional energy targets

Different scenarios were compared in Figure 7.4 to better understand the effects of i) oil sources shutdown, ii) ESS deployment, iii) increasing the installed nuclear capacity and iv) adopting

national energy targets. Since the different 2023 grids satisfied the same total demand, their emission patterns were similar yet scenario 1 was the most impactful.

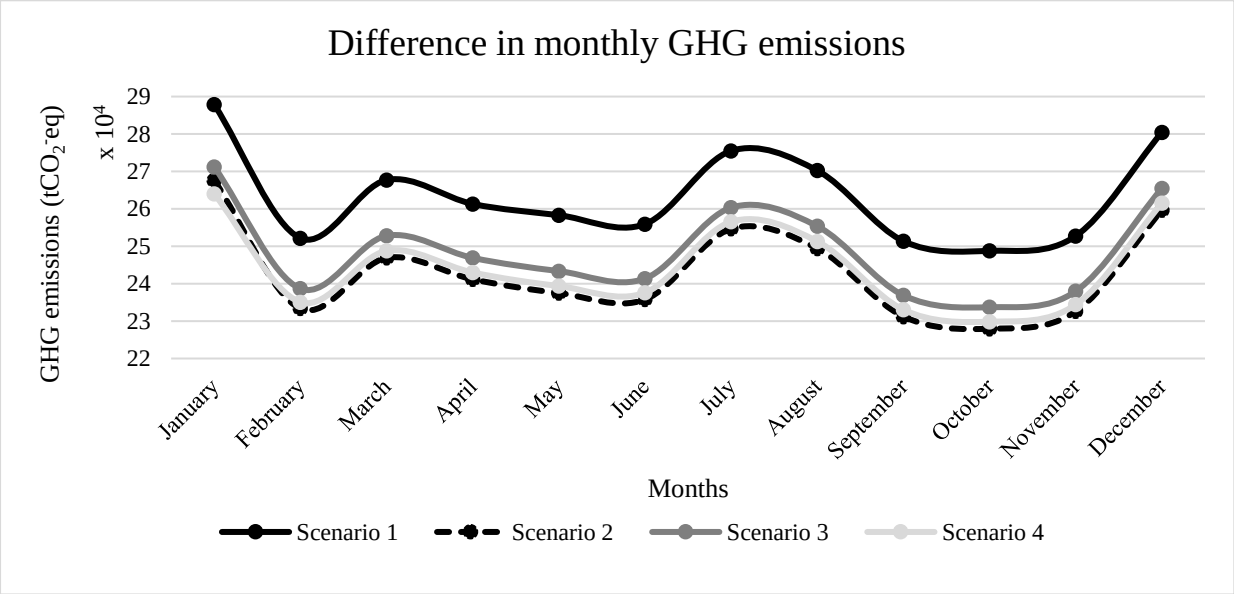

Figure 7.4 Difference in the monthly GHG emissions between the default 2023 grid in scenario 1 and regional scenarios 2, 3 and 4. The y-axis does not start at 0 for visualization purposes.

Role of oil sources

Scenarios 1 and 2 were compared to understand how the shutdown of oil sources affects the grid operation and environmental profile. All oil technologies were excluded from the 2023 grid in scenario 2, except for combustion turbines.

The oil generated electricity in the default grid contributed only 0.2% of the total annual electricity produced in Normandy. This is explained by its nearly negligible installed capacity (35.8 MW) as compared to other sources (e.g. 10 640 MW for nuclear power).

At the emissions level, oil sources are responsible for 8% of the total grid CO_2-eq emissions. In the zero-oil case, nuclear and natural gas (NG) sources compensate for the minimal difference in generation caused by the shutdown of oil power plants. Hence, oil technologies can be easily decommissioned to save these emissions while barely affecting the remaining dispatchable sources.

Furthermore, additional monetary savings can be anticipated upon their shutdown, since these sources are very impactful, and the cost of their emissions is high.

Role of ESS

Since the French government is currently investing in energy storage technologies (Clercq, 2018), it will be interesting to evaluate how the addition of batteries could affect grid GHG emissions. The deployment of Li-ion batteries highlighted the impact of ESSs on the 2023 grid generation patterns and emissions between scenarios 1 and 3.

At the generation level, the batteries substitute most of the electricity production from oil sources. In the default 2023 scenario, oil contributes to 0.2% of the total generation, whereas, in the ESS scenario, the share of oil decreases to 0.05% and the batteries deliver the remaining 0.13%.

This substitution in terms of generation reflects on the emissions as well. The addition of batteries reduces the overall grid emissions by 6%. The share of oil from the total grid CO_2-eq emissions is reduced from 8% to 2.33% when the ESS is deployed. Yet, the ESS alone is incapable of replacing the oil sources all the time. During certain periods, demand is satisfied by NG or nuclear power, whose emissions increase by 1% and 2.5%, respectively. Therefore, the addition of batteries has a similar impact on the grid's environmental performance as the shutdown of oil sources

Role of increased nuclear power

Scenarios 1 and 4 were compared to understand the effect of the increased generation of electricity from nuclear sources in the eventual case where the Flamanville 3 reactor begins operation prior to 2023. In terms of generation, the increase in installed capacities from 10 640 MW to 12 290 MW enables more generation from nuclear sources. The share of nuclear power from total generation increases by 0.15%, whereas the share of oil sources is reduced from 0.2% to 0.05%. This means that the additional reactor further supplies the demand and decreases the grid's dependence on oil sources.

Being less emitting than fossil fuels, nuclear power is favored as an electricity generation source. At the emissions level, this substitution of oil sources at different periods in the year decreases the total grid CO_2-eq emissions by 6%. However, the share of nuclear sources from the total emissions

increases by 2.75% when Flamanville 3 is in operation. The concerns, therefore, arise in terms of resource depletion and the need for an efficient solution for nuclear wastes.

7.4.2.2 Role of national energy targets

In scenario 5, the Norman grid was modelled according to the national energy targets.

At the consumption level, the forecasted annual total electricity consumption is expected to drop by over 11.45%, so the first national target is achieved. For fossil fuels, the national goals recommended a reduction of 33.64%, 21.27%, and 14.36% from oil, coal, and NG respectively.

According to our model, the generation from these sources dropped by 90.05%, 72.9%, and 69.59%, as compared to 2013 thereby meeting the national goals of the generation of electricity from fossil fuels. This is explained by the future increase in emission taxes, which will catalyze the grids' shift from fossil fuel technologies. In terms of nuclear power, the national aim is to reduce its contribution to 55.4% of the annual average consumption. According to the results of the optimization, the share of nuclear power is anticipated to be 91.06%in 2023. The shift from the reliance on fossil fuels with a relatively low increase in the share of RESs (as compared to the regional goals) would increase electricity production from nuclear sources to ensure the power balance between demand and supply. Nuclear generation reduction targets would therefore not be met without further investments in the renewable energy sector and the deployment of new technologies such as ESS.

The comparison of scenarios 1 and 5 was at the installed capacity targets, generation, and emission levels. For the planned installed capacities, the comparison between the national and regional targets is mainly focused on the RESs (see Table 7.2 for the difference in RES targets). The discrepancy in the planned installed capacities between the scenarios is especially perceptible at the wind and solar power levels, two technologies that are expected to transform the future of the global electricity generation.

Owing to its geographic location, Normandy has a high potential for wind farm development, especially offshore. Generalizing the goal will, therefore, hinder the regional investment in these technologies at full capacity. A similar conclusion applies to solar power since Normandy has

already achieved 25% of the targeted installations. As for hydropower, the installed capacity in 2018 already exceeded the national target for 2023 by 12%. Bioenergy sources are expected to reach similar targets at both levels. The targets have therefore to be tailored to regions and adapted to their geographic locations to maximize the benefit of RES installations and reduce CO_2-eq emissions from the electricity generation. Since the RESs are being deployed at an accelerated pace, making regular updates to national legislation is mandatory.

While no fossil fuels were decommissioned in the national scenario, only NG and combustion turbine oil technologies remained operational in the default 2023 scenario. This justifies the high share of fossil fuels from generation: 0.9% for scenario 1 vs. 2% for scenario 5.

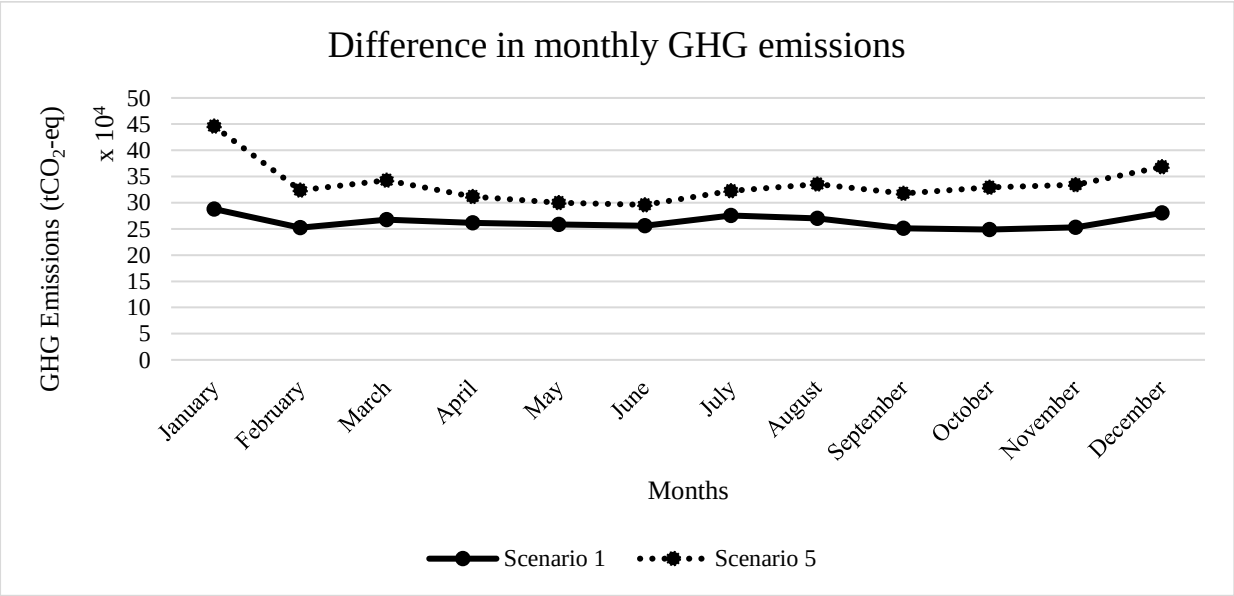

Figure 7.5 Difference in total monthly GHG emissions between scenarios 1 and 5.

The higher share of fossil fuels in the national scenario affected the grid environmental profile (Figure 7.5). The annual average GHG emissions in the national scenario are 24% higher compared to the default 2023 scenario. This is attributed to the difference in operating sources which include more fossil fuels and less RES in the national scenario.

Despite accounting for only 2% of the total generation of the 2023 national grid, fossil fuels lead to over half of the grid total annual GHG emissions because of the high emission factors of oil and coal sources. The decommissioning of oil piston motors, vapor cogeneration technologies, and coal plants reduces the share of fossil fuels from the total generation and emissions by half. The

combustion turbine oil plants that remain in operation account for 2.33% of the total emissions, whereas the rest is attributed to natural gas sources. In the default 2023 scenario, the increased installed capacities of RESs compensate for the removed sources and reduce the share of generation from nuclear plants as compared to the national scenario.

National goals have a greater impact on the climate change category as well as different endpoints (Table 7.5). The difference is explained by the higher share of fossil fuels and the lower share of RESs in scenario 5. However, these results are based on the optimization of grid operations in terms of CO_2-eq emissions. It would be of great interest to investigate how the overall grid emissions are altered when optimized in terms of the remaining impact categories.

Table 7.5 Difference in total annual impacts at the different endpoint categories between scenarios 1 and 5.

Scenario	**Total annual impacts**			
	CC (tCO_2-eq)	**HH (DALY)**	**EQ ($PDF.m^2.yr$)**	**R (GJ)**
Scenario 1	$3\ 162 \times 10^3$	15 045	$8\ 599 \times 10^6$	$1\ 655 \times 10^6$
Scenario 5	$4\ 028 \times 10^3$	16 262	$9\ 589 \times 10^6$	$1\ 846 \times 10^6$
Difference	24%	8%	11%	11%

Both targets may be used to model future power grids. Yet, regional goals provide a higher level of accuracy since they consider the specifications, economies, and geographies of the regions under assessment. Still, rather than basing the study on assumptions, national goals are adequate when no other data are available.

7.4.2.3 Comparison at the endpoint level

The total annual impacts on CC, HH, EQ, R in the various regional scenarios were analyzed in order to go beyond the impacts of climate change (Figure 7.6).

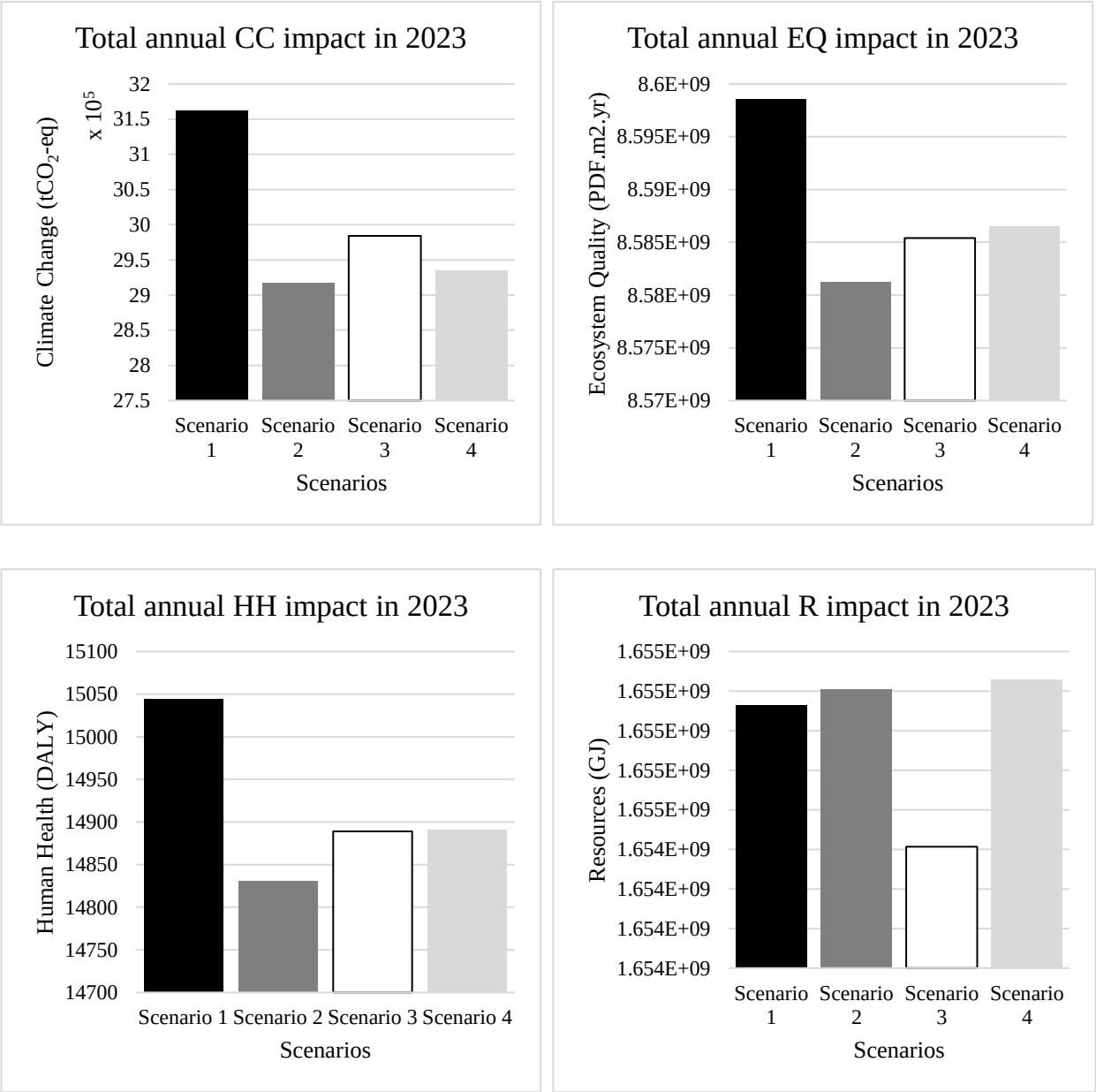

Figure 7.6 Variation in total annual emissions at the different endpoint categories between scenarios 1 to 4 (a) for climate change (CC), (b) at ecosystem quality (EQ), (c) at human health (HH) and (d) at resource depletion (R)

Comparison at the **climate change** level

The default 2023 grid, results in the highest annual CO_2-eq emissions. This is attributed to the extensive oil power plant operations compared to the other scenarios. In scenarios 2 and 4, nuclear

sources primarily substituted electricity generation from oil, thus reducing the total grid emissions. In scenario 3, electricity generation from oil was mainly substituted by the ESS, which cannot always replace fossil fuel sources. The savings in terms of CO_2-eq emissions were therefore not as significant as in scenarios 2 and 4.

Comparison at the **ecosystem quality (EQ)** and **human health (HH)** levels.

The default 2023 scenario has the highest annual impact on ecosystem quality and human health. The complete decommissioning of combustion turbines reduces the impact on ecosystem quality and human health the most since no oil burning is involved. Scenarios 3 and 4 also result in lower impacts as compared to scenario 1, although the impact is lower since the oil power plants are still in operation. To further improve the environmental impact of the grid at these categories, we recommend the complete decommissioning of oil sources.

Comparison at the **resource depletion (R)** level.

In the increased nuclear scenario, generation from nuclear power plants increases, leading to an additional demand for nuclear fuel which necessitates further uranium mining. This explains the greater grid impact in terms of resource depletion. Similarly, in the zero-oil scenario, NG and nuclear sources compensate for the complete decommissioning of oil plants thus requiring more gas and uranium. Comparing scenarios 1 and 3, the batteries deployed in the grid partially replace generation from oil lowering the impact of the grid in terms of resources since less oil is required. However, the manufacturing of batteries also necessitates some resources, which explains the higher total annual impact in this endpoint category relative to the ESS scenario.

7.4.2.4 Costs comparison.

Electricity production under the different scenarios resulted in analogous cost reductions. Compared to 2018, the total cost of operation decreased by 19%. While the cost of generation was reduced by 14%, the cost of GHG emissions witnessed a greater reduction and dropped between 47 and 50% depending on the scenario investigated. The variations are attributed mainly to the shutdown of coal power plants and partial decommissioning of oil sources. These fossil fuels, despite their cheap costs of generation, have more impact on the climate change level. Their emission costs are 30 and 16-fold the costs of nuclear and natural gas sources respectively. With

tighter environmental constraints and additional taxes, it is no longer enough to solely minimize the costs of generation. There is a need to optimize the operation of conventional sources, enhance their environmental profiles or even ditch them completely, in order to guarantee cheap and clean electricity.

7.4.3 General discussion

To further understand the future grid, the variability of the GHG emissions was assessed. Human behavior, among others, dictates electricity generation patterns. Hence, the resulting emissions depend on the consumption levels throughout the day. The highest difference in emissions is reached between 3-6 p.m. and correlates with when electricity consumption peaks (Figure 7.7). On the other hand, the lowest variability in emissions is at 10 a.m. when the demand is low. The range of emissions is therefore affected by the difference in consumptions at various moments of the day, weekdays, weekends and seasons.

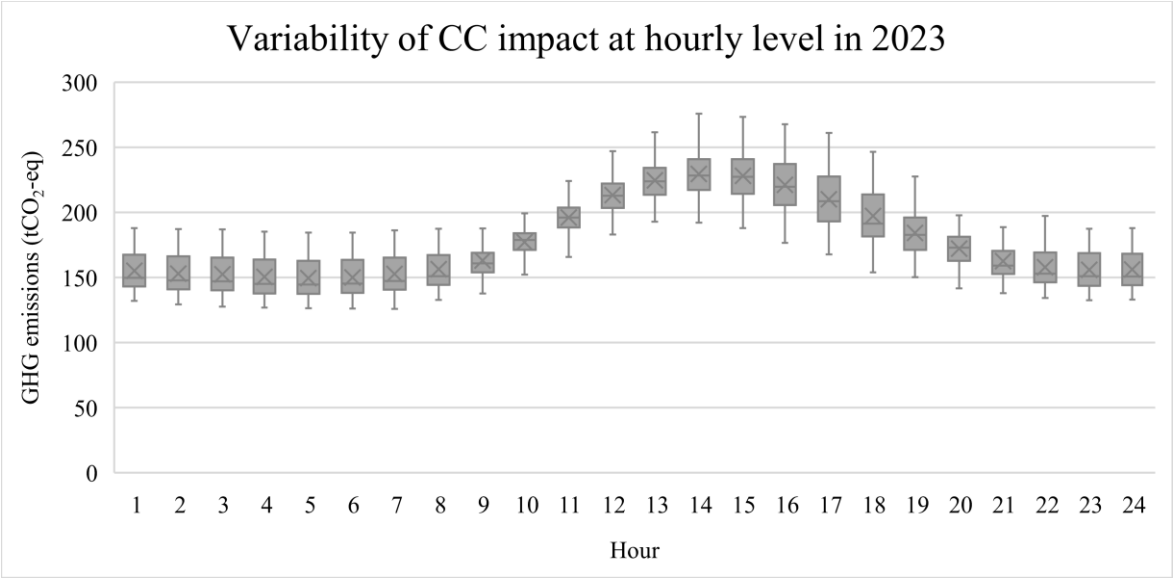

Figure 7.7 Variability of climate change impact at the hourly level for the default 2023 Norman grid.

Beyond its results, this prospective analysis of the 2023 Norman power grid can contribute to the debate on the implementation of new technologies and the overall energy transition in the region. It also provides a clearer understanding of the influential decisions affecting the environmental

profile of the future Norman grid. The developed methodology can serve as a pre-screening tool to narrow choices and improve the decision-making process.

7.4.4 Advantages and limitations of the approach

Advantages

The new methodology enhances the assessment of future power grids and overcomes several limitations of the existing tools:

- Compared to the LCA/ESMs method: The modification and application of the O-C-LCA in a prospective context is simple, less time-consuming and easy-to-use. It facilitates the modelling of electricity generation and provides an overview of the future impacts at different levels. The developed method aims to complement energy system models and serves as a preliminary evaluation step to highlight the operating conditions worth further exploration. It helps identify relevant future scenarios and appropriate investments so the prospective assessment can be more focused. Therefore, it enables a holistic evaluation of the environmental profiles over the short-term.
- Compared to the conventional environmental scenario analysis method: The O-C-LCA presents several advantages over this tool. It ensures a more detailed modelling of future grids since the scenarios are developed using an optimization algorithm. Rather than setting assumptions or having a single average value for the year, the results better represent the temporal dynamism of the electricity generation. It enhances the prospective assessments and makes it possible to evaluate installed capacity goals and emission targets in an optimized mode of operation.
- Ease of application and modification: O-C-LCA can be easily updated to provide a better assessment and understanding of potential hotspots. If historical and forecasted data is available and the specifications of the future energy system are determined, the adaptation of the methodology to other systems becomes possible. Grid operators can, therefore, evaluate their actions in the short-term to ensure the fulfillment of their long-term energy objectives. The O-C-LCA hence supports policymakers and governments seeking to take preventive measures.

Limitations

Despite its advantages, the developed method has some limitations, including the following:

- Uncertainty: The future is always uncertain and so are future consumer demands. The weather conditions and RES operations used in the calculations are not expected to occur as modelled and the results per time slot are therefore inaccurate. However, considering the annual period could reduce this uncertainty by converging the weather conditions and RESs operation to their average values. Moreover, since the results are based on historical data, the future effect on climate change may be underestimated.
- Lack of economic details: Unlike the ESMs (e.g. TIMES), the method does not consider all the market details and economic factors, such as depreciation rates.
- Change in neighboring grids: To better account for the trades, we would have to check the energy policy of every region to which Normandy exports electricity. If the neighboring regions import less from Normandy, the resulting GHG emissions from electricity production will be reduced.
- Environmental evaluation: Power technologies in use may change over the next five years, and estimating their environmental impacts based on current life cycle inventory data may not be the best practice. Introducing data specific to new power generators would improve the quality of the results.

7.5 Conclusion

In this manuscript, a novel method consisting of a simplified optimization approach combined with LCA and environmental scenario analysis was presented to support policymakers in the energy sector. It has a profound policy implication, serves as a preliminary evaluation of energy plans in the short-term and reduces the complexity of estimating the environmental performances of future power grids.

The results demonstrated that the operation of the optimized 2023 Norman grid can reduce CO_2-eq emissions by 64% compared to 2018 due to an increase in RESs contribution from 3.3% to an expected 17% in 2023. The shutdown of coal power plants is expected to enhance the carbon

footprint of the grid and the oil combustion turbines can be excluded without affecting grid stability. The deployment of an ESS can lower the grid's impacts on the different endpoint categories and if the Flamanville 3 reactor is put into service, additional environmental benefits may be expected. In terms of targets, results point out to regional goals being favored, since they are tailored to the geographic locations under evaluation and will enable grid operators to maximize their generation potential from certain sources. Yet, it would still be beneficial to rely on national targets to avoid assumptions when no other data are available. In terms of costs, the shutdown of coal plants and some oil sources can reduce the total grid operation cost by nearly 19%.

Finally, we acknowledge that prospective evaluations are associated with a high degree of uncertainty. However, policymakers need to foresee the future environmental impacts of their strategies since early decisions have a far-reaching influence on the success of energy plans. Our analysis helps identify solutions that hold the greatest potential to transition to a more sustainable electricity mix. Once adapted, its application to other power grids in different geographical locations is worth investigating.

Acknowledgment

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CHAPTER 8 GENERAL DISCUSSION AND RECOMMENDATIONS

8.1 Achieving the research goals

The aim of this thesis, developing a new life cycle assessment method to evaluate and compare the potential environmental impacts of energy storage systems in power grids, was achieved through the fulfillment of the three sub-objectives.

This chapter discusses the findings of Chapters 5 to 7, presents the limitations faced and proposes some recommendations for future work.

8.1.1 Achieving sub-objective 1

A new LCA methodology, the optimized-consequential LCA, was developed in Chapter 5 to improve the assessment of electric grids and new technologies such as energy storage systems. ESS in general and lithium-ion batteries, in particular, will play a major role in the future grid. There is a need to improve their modelling and environmental assessments in order to better understand the consequences of deploying these systems and to support decision-makers in their choice of the most profitable technology (Pellow, Ambrose, Mulvaney, Betita, & Shaw, 2019).

The common practices in the literature include:

- Cradle-to-gate assessments, where the use phase of the batteries is excluded from the assessment. This approach is not recommended since a technology that is advantageous at the manufacturing level might have low efficiency leading to reduced avoided impacts from its operation. Hence, to have a more holistic assessment of the different alternatives, this life cycle step needs to be considered.
- Assumptions, where the avoided impacts from the use phase of the ESS are based on the existing technologies. In this practice, LCA practitioners attribute a specific percentage of electricity generation to the ESS and assume that it replaces the same percentage of generation from other sources. This method is not recommended since ESS are not charged from one single source and do not replace a specific technology throughout the entire year
- Extrapolations, where the operation of ESS in the grid is extrapolated from the operation of batteries in electric vehicles. Such a method is not reliable, because the conditions of

operation are very different, they would affect the cycling of the battery and consequently alter the avoided impacts from its operation.

- Post-deployment assessments, where the avoided impacts from the ESS operation is estimated based on its historical operation. These studies are relevant to understand the environmental profile of the ESS operation in determined locations under specific conditions. However, to support decision-makers, studies need to be prospective and tailored for the region under assessment.

The developed method overcomes the limitations of the current LCA practices regarding future deployments of ESS in the power grid. The optimization step facilitated the modelling of the ESS operation while considering the grid constraints. The battery was charged by various sources and was discharged at different moments throughout the year. The avoided impacts from the operation of the batteries were more accurately estimated due to the enhanced representation of their temporally-variable operation and the life cycle assessment results of the ESS were therefore improved. This study is highly relevant for decision-makers because batteries are increasingly being deployed in various sectors such as mobility and industrial processes and the understanding of the environmental consequences has become crucial (Guney & Tepe, 2017).

8.1.2 Achieving sub-objective 2

The LCA methodology developed in Chapter 5 was expanded in Chapter 6 to include additional costs in the optimization algorithm. Several studies, such as (Hiremath et al., 2015; Patrizio et al., 2017), highlighted the need for detailed life cycle assessments of the batteries for more major environmental impact categories since the reliance on climate change alone is no longer satisfactory. Therefore, the evaluation of lithium-ion batteries operation went beyond the assessment of GHG emissions.

Status of the current studies:

- Limited assessment of electric grids while accounting for externalities. In most researches, the focus is on climate change and very few studies have analyzed the consequences of internalizing externalities on the life cycle emissions of the various operating technologies.

- Lack of ESS use phase assessment when the externalities are internalized. In most cases, the life cycle impacts of batteries operation are not adequately modelled nor evaluated. While only a few studies accounted for the consequences of externalities on the operation of the different power sources, none have evaluated the effect of their consideration on the ESS use phase.

The developed methodology in the sub-objective allowed the evaluation of the electric grid when the external costs of the generation were internalized. The consequences of including the externalities on the operation of the various sources were highlighted and the compromise between the existing technologies to deliver the optimum electricity in terms of all impact categories was underscored. As for the ESS use phase, its assessment was further improved. The new method allowed us to more accurately assess and better understand how the internalized externalities alter the avoided impacts and potential cost reductions from the operation of batteries.

8.1.3 Achieving sub-objective 3

The third sub-objective consisted of applying the developed methodology in a prospective context. The methodology developed in Chapter 5 was modified to account for future energy policies and emission targets through the addition of an environmental scenario analysis step. The policymakers need a practical decision-making tool, applicable to the short-term and capable of reflecting the optimization and dynamism of the power sector. Prospective assessments of the energy systems often rely on energy system models.

The common practices of relying on ESMs are limited by:

- Their complexity: Building and running an ESM is complicated and necessitates a tremendous amount of data
- Their runtime: Assessing the future energy system using ESM is time-consuming
- Their time-frame: ESMs are generally designed for mid to long-term assessments

To overcome these limitations, a new method of reduced-complexity was developed to prospectively assess the electric grids in the short-term. The most challenging part is the identification of future values. While there might be information on the projected installed capacities and technologies, information regarding future demand, weather conditions, costs, and

emission factors are debatable. Yet the developed method can serve as a prescreening tool for decision-makers to evaluate their targets early in the decision-making process and adapt them accordingly. The modified O-C-LCA also allows the comparison of various future scenarios and identification of those worth further exploration.

8.2 Limitations

The methodology developed and the results obtained rest on the validity of a number of assumptions. As such, there are still a few limitations associated with this research at the methodological and case study levels and they are explored hereafter:

8.2.1 Limitations of the methodology

The optimization function aimed to minimize the total cost of electricity generation including the production and damage costs. However, the values used in the optimization were European average costs. Since no data were available for the French market per se, the use of these average values was an acceptable assumption. Yet, it would be of great interest to include costs corresponding to the grid under evaluation since some technologies available locally might be cheaper than in the rest of Europe and the results can therefore differ.

Furthermore, the optimization of electricity generation was mainly for dispatchable power sources since their operation can be controlled. However, accounting for the costs of renewable energy sources can significantly influence the decisions of grid-operators. Despite having negligible damage cost at the various impact category levels, the RES cost of manufacturing is still high. In order to have a more holistic assessment and better estimate the economic benefits of the energy transition, these costs need to be included.

Another factor that wasn’t accounted for in the study is the power grid losses. All the produced electricity was assumed to satisfy the demand. However, this might not be representative of reality. Since the electricity is generated at different locations in the region, additional electricity will be produced to compensate for the losses from transmission lines.

In terms of uncertainty, there were two main limitations associated with the future grid assessment and the external costs used.

The future is always uncertain and therefore prospective assessments are inherently uncertain. To overcome this limitation, studies need to be updated whenever more accurate information is available. This includes the different technologies assessed, their specs, their emission factors, and the projected electricity demand as well. Despite this uncertainty, prospective studies are still useful to provide decision-makers with an overview of their potential environmental impacts. The other uncertainty is associated with the external costs of electricity generation technologies. The quantification of damage to human health and ecosystem quality can be very different from one approach to the other. The methods used to monetize these damages can also significantly vary according to the assumptions made. Therefore, the discrepancy in the results will be high and different conclusions will be reached. This will limit the comparison of one study's outcome to another unless they rely on similar methodologies and hypotheses.

8.2.2 Limitations of the case study

One major limitation related to the assessment of the case study is the reliance on a generic database for the manufacturing of batteries. Since industry data are lacking, the inventory was retrieved from literature. Such an assumption can result in the underestimation of the impacts related to this life cycle step. It would be of great importance to rely on up-to-date industrial data and avoid the use of the electric vehicle battery inventory.

Furthermore, detailed studies on the end-of-life of grid-scale battery storage are missing (Pellow et al., 2019). To evaluate the environmental impacts from this step, the batteries were assumed to be entirely disposed. However, if the end-of-life processes included recycling, further environmental benefits might result and alter the findings.

Battery losses were not considered in the assessment as well. This assumption was mainly due to the choice of lithium-ion batteries which have a 90% roundtrip efficiency leading to minimal losses (less than 1%/month) (Bhatnagar & Loose, 2012). However, to better estimate the avoided impacts from the ESS operation, this parameter needs to be included in the assessment. Furthermore, this assumption limits the comparison of results with other battery technologies. The difference in batteries efficiency would impact the calculated avoided emissions and therefore reduce the accuracy of the results.

The size of the energy storage system deployed was also a limitation in this study. Since the determination of the ESS size was outside of the scope of this research, its capacity was estimated based on the data of the power grid in Normandy. To improve the accuracy of the findings, a proper sizing step needs to be performed.

Finally, we recognize that the developed method is not perfect; yet it was capable of providing useful insights on the assessment of energy storage systems and power grids regardless of its limitations.

8.3 Recommendations

In light of the aforementioned limitations, several recommendations for future work at the methodological and case study levels are presented hereafter.

At the methodological level, we recommend:

- Relying on a multi-objective optimization

In this project, impacts were monetized, and a single-objective optimization problem was solved. It would be of interest to see how the results and conclusion of the study would differ if weights were assigned to the various impact categories to solve a multi-objective optimization problem.

- Assessing various monetary valuation methods

The external costs of electricity generation used for the optimization were estimated using the ExternE method. It would be of interest to compare the cost of impacts obtained using other methods such as the choice experiment and budget constraint and highlight the difference in the findings.

- Developing an agreement for impact monetization methods

Until today, there is no agreement in the scientific community on the most suitable monetization method for evaluating environmental impacts in LCA. (Nguyen et al., 2016)

- Accounting for additional impacts

In most energy system assessments, the focus is on the evaluation and reduction of climate change impacts. While only a few studies account for the damages on human health and ecosystem quality, the impacts on the resource depletion are overlooked. It would be of interest to further investigate this category and account for it in the optimization of the power grid operation. With countries like France investing in nuclear power, such an assessment is needed to better understand the environmental magnitude of the decision.

Rare earth elements are also a topic worth further exploration. These elements are the main component of lithium-ion batteries and they are increasingly being extracted and used in their manufacturing. However, studies assessing the environmental impacts of these elements throughout their entire life cycle are very limited.

- Evaluating various geographical locations

The methodology developed in this thesis can be further applied to power grids in other geographical locations and serve as a common ground for their comparison. It can be easily adapted to new case studies and can serve as a preliminary assessment for the energy plans. It can also provide the grid-operators with an overview of the grids' environmental profile when new technologies such as energy storage systems are added.

At the case study level, we recommend:

- Including further evaluation factors

Additional factors can be taken into account when assessing batteries for grid-scale applications. To support decision-makers in the selection of ESS and improve the results of their assessment, parameters such as investment costs and accurate battery sizing need to be considered.

- Applying the developed method to assess other technologies

The assessment focused on lithium-ion batteries since they dominate the grid-scale storage nowadays. However, new technologies are penetrating the market and it would be of interest to assess them and compare their environmental impacts, at the various life cycle stages including the use phase.

- Using data from the industry

In the literature, only 5 studies provide detailed inventory data on the manufacturing of lithium-ion batteries, none for grid-scale applications (Peters & Weil, 2018). To further improve the accuracy of the results, it is recommended to rely on up-to-date industry data.

- Looking at the end-of-life of batteries

The end-of-life of batteries is overlooked in almost all studies and information about their disposal and recycling is missing. In order to have a holistic assessment, analyzing the environmental impacts from this life cycle step would be of great interest.

- Looking at second-life batteries

There are recommendations to re-use electric vehicle batteries at their automotive end-of-life into stationary applications. Since the extended life of these batteries is expected to reduce their life cycle environmental impacts, it would be of interest to assess their environmental profiles and compare their corresponding avoided emissions with that of new batteries.

CHAPTER 9 CONCLUSION

This research work and its contributions have enabled the achievement of the main research objective of developing a new life cycle assessment (LCA) method to evaluate and compare the potential environmental impacts of energy storage systems (ESS) in power grids. The methodological developments in this work allowed:

- The incorporation of the temporal aspect of ESS in its environmental evaluation. A new life cycle assessment method, the optimized-consequential LCA (O-C-LCA), was developed. It consists of soft-linking an optimization algorithm with the life cycle assessment to incorporate the temporal variability of the power grid and model the ESS operation under grid constraints. By better representing the use phase of large-scale ESS, it became possible to assess the potential environmental impacts from this life cycle step more accurately.
- The integration of the external cost of electricity in the assessment of the ESS use phase. The costs of damage to the ecosystem quality and human health in addition to climate change were added to the cost of production when optimizing the electricity generation. The internalization of these costs affects the generating sources and consequently changes the environmental profile of the ESS use phase. Accounting for externalities is important to better assess the potentially avoided environmental impacts from the operation of ESS in power grids and improve its life cycle analysis.
- The elaboration of a framework for the evaluation of power grids in the short-term. An additional environmental scenario analysis step was added to the O-C-LCA for its application in prospective contexts. The new method allows the development of different future electricity generation scenarios, the optimization of their operation and the assessment of their potential environmental impacts. Different energy goals and alternative technologies such as energy storage systems can be therefore compared to support decision-makers. The new method serves a preliminary evaluation step for the policymakers to assess their targets, adjust them early in the decision-making process and identify the solutions holding the greater benefits to society.

Despite the methodological improvements, this research was constrained by several limitations. Future assessments are inherently uncertain and can be influenced by numerous factors such as market prices, weather conditions, and political stability. For the assessment of the batteries and the estimation of external costs, several assumptions were made and generic databases were used. The discrepancy between the scenarios evaluated and reality might alter the results and affect the conclusions. Data specific to the case study, and region-specific emission factors and costs are therefore required to improve the accuracy of the findings. The scope of the study can be further broadened to perform additional research. The inclusion of resource depletion in the optimization of power grid operation is recommended to better understand the impacts of future technologies. Additional energy storage systems need to be evaluated and their life cycle impacts need to be compared to identify the most profitable technologies. Estimating the external costs of electricity generation using different monetization methods is of great importance as well and need to be investigated to highlight the impact of these values on the results. Finally, for the energy storage systems, the evaluation of second life-batteries is advised.

The methodological development of this research contributed to the environmental assessment methods of energy storage systems and power grids in order to serve the ultimate goal of supporting policymakers and improving the decision-making in the energy sector. And, in the end, "*Decisions will always have to be made based on incomplete knowledge of their consequences"*

Thomas Ekvall

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APPENDIX A SUPPLEMENTARY MATERIAL PUBLISHED WITH CHAPTER 5 (A)

Calculation data for the power sources

For the dispatchable power sources:

Table A. 1: Data of dispatchable sources

Technology	Installed capacity (MW)	Cost of production (€/GWh)	Lower generation limit (MWh)	Upper generation limit (MWh)	Emission factors (tCO2/MWh)
Nuclear	11600	0.035	2173	9200	0.0123
Natural Gas	622	0.042	88.43	568	0.6068
Coal	612	0.033	87.57	574	1.0517
Thermal	1238	0.034	176	1142	0.8282

For renewable energy sources:

Table A. 2: Data for renewable energy sources

Technology	Installed capacity (MW)	Upper generation limit (MWh)	Emission factors (tCO2/MWh)
Solar	131	108	0.0819
Wind	725.5	672	0.0139
Hydro	49.6	31	0.0043
Bioenergy	114	71	0.2131

APPENDIX B SUPPLEMENTARY MATERIAL PUBLISHED WITH CHAPTER 5 (B)

LCA steps of BESS

The life cycle steps of the battery energy storage system are represented in the figure below:

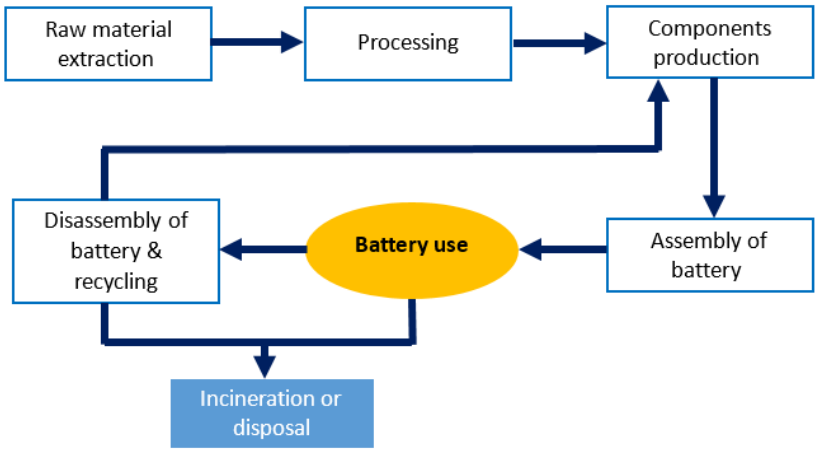

Figure B. 1: Life cycle stages of ESS

The stages covered by the assessment of the BESS are:

- Battery Manufacturing (including raw material extraction, processing, components production, and assembly)
- Battery Optimized Use phase
- Battery End of Life (EoL) (Only incineration considered)

- *Assessment of the BESS manufacturing*

The data for the Li-ion batteries was retrieved from the supplementary information of:

Peters, J. F., & Weil, M. (2018). Providing a common base for life cycle assessments of Li-Ion batteries. *Journal of Cleaner Production*, *171*, 704-713.

The batteries chosen are lithium-iron phosphate (LFP). Hence, the inventory was adapted from the supplementary information of:

Majeau-Bettez, G., T.R. Hawkins, and A.H. Stromman, *Life cycle environmental assessment of lithium-ion and nickel metal hydride batteries for plug-in hybrid and battery electric vehicles.* Environ Sci Technol, 2011. **45**(10): p. 4548-54.

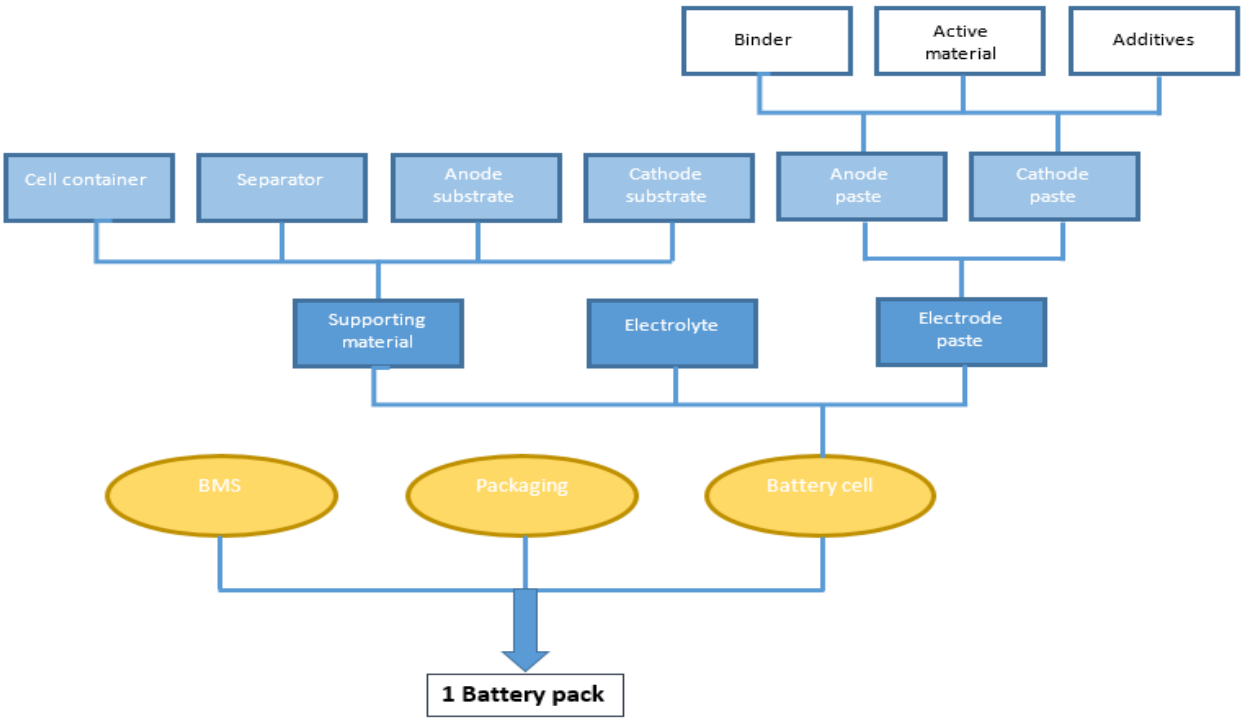

Figure B. 2: Components considered in the battery's manufacturing

Figure B.2 details the material considered in the manufacturing of the BESS. Some components values and providers were substituted whenever a more detailed and comprehensive information was available. Afterward, Peters & Weil compiled the data in a new LCI.

- *Evaluation of the BESS use phase*

The use phase was modeled in the paper following the developed approach by means of the optimization algorithm. The steps to calculate the saved emissions per 1 kg of battery pack for the use phase are as follows:

1- Sum the saved emissions at every time interval during the year 2017 to obtain the total value (30.3129 tCO_2)

2- Convert the total amount of saved ton of CO_2 into kg (30 312.86 kgCO_2)
3- Divide the kgCO_2 saved by the number of battery units (250 packs) to obtain 121.251 kgCO_2 saved/battery pack.
4- One battery unit weighs 39.5 kg, so the amount of saved emissions per 1 kg of battery is $\frac{121.251}{39.5}$ = 3.069 kg CO_2 saved/ kg battery pack/year
5- Since they are saved emissions, they are expressed negatively, so = -3.069 kg CO_2 saved/ kg battery pack/year

- *Analysis of the BESS EoL*

According to the Environmental Protection Agency (EPA), batteries are classified as Municipal Solid Wastes. Currently, as per the data of Umicore, only 5% of Lithium-ion batteries are being recycled and the rest is incinerated and landfilled. Since there is a lack of data regarding the end of life of Li-ion batteries at the grid scale level, they are considered to be entirely incinerated. The process considered to assess the emissions resulting from the incineration of 1 kg of municipal solid waste in ecoinvent for France is:

treatment of municipal solid waste, incineration | municipal solid waste | cut-off, S

APPENDIX C SUPPLEMENTARY MATERIAL PUBLISHED WITH CHAPTER 7 (A)

2023 grid and calculation details

- **Adjusted annual consumption in Normandy**

Over a period of 10 years (between 2007 and 2017), the adjusted consumption in Normandy changed only by 1.4% (RTE), which makes it relatively constant. The historical consumption values are presented in Table C. 1

Table C. 1: Historical adjusted consumption in Normandy between 2006 and 2017

Year	Adjusted annual consumption (TWh)
2006	25.7
2007	26.3
2008	26.5
2009	26.4
2010	26.1
2011	26.3
2012	26.2
2013	26.4
2014	26.4
2015	26.6
2016	26.7
2017	26.7

2018	25.9

- **<u>Evolution of non-dispatchable power sources</u>**

➢ Calculation of the installed capacities of the 2023 grid

The scenario presented here is based on Targets for Normandy in "Le baromètre 2018 des énergies renouvelables électriques en France" report (Courtel et al., 2018). The information available is for the years 2020 and 2050. The information provided could then be used to obtain, by linear interpolation, the data for 2023.

Table C. 2: RES installed capacities in 2020, 2023 and 2050

Source	2020 installed capacity (MW)	2050 installed capacity (MW)	2023 installed capacity (MW)
Wind	1930	20900	3827
Solar	670	22100	2813
Hydro	100	100	100

The information for bioenergy isn't available so it was based on France's growth percentage.

- **<u>Evolution of the dispatchable power sources</u>**

In 2023, the dispatchable power sources in Normandy will change due to the energy plans and emissions goals set.

➔ For the **coal power sources**

The French government aims to shut down all working coal power plants by 2022 *(WNN, November 2018)*. Hence, the Norman grid mix of 2023 (scenarios 1 to 4) excludes this

technology. For scenario 5, the installed capacity of coal power is considered the same as in 2018.

➔ For the **oil power sources**

In what concerns the oil power plants, the French government announced their decommissioning starting back in 2016 *(METS, 2016)*. Hence, for the 2023 grid of scenarios 1, 3 and 4, we only consider oil combustion turbine plants to be in operation. In scenario 2, we investigate the impact of their complete decommissioning. In scenario 5, two more oil technologies are considered: vapor cogeneration and piston motor.

➔ For the **nuclear power sources**

As per the national goals and declaration of the French president, 4 to 6 nuclear power plants will be shut down by 2030 and 14 by 2035 *(WNN, November 2018)*. By 2020, only Fessenheim power plants will be decommissioned and the remaining plants are scheduled as follows: two between 2025 and 2026, two between 2027 and 2028. Therefore, in 2023 the nuclear source of Normandy won't be affected, and the operating capacity will remain as it was back in 2018.

➔ For the **Flamanville 3** case

For the Flammanville 3 scenario (scenario 4), we assume that the Flamaville 3 nuclear reactors, currently under construction and testing (EDF, 2019; PowerTechnology, 2019), will enter operation. Hence, the installed capacity of nuclear sources will increase to 12 290 MW. The new upper and lower generation limits of this power source are therefore 10 627 MW and 2 352 MW respectively.

➔ Costs of generation

According to the French ministry of ecological transition and solidarity (METS, 2016), the marginal cost of generation from **nuclear sources** is 12 €/MWh and for **gas sources,** the cost

ranges between 35 and 45 €/MWh, so we considered 40 €/MWh. As for the **oil** and **coal sources**, the prices considered were 30 and 22.5 €/MWh respectively.

- **<u>Constraints of the grid optimization</u>**

The optimization algorithm provides the generation patterns only from the dispatchable sources since these are the sources over which grid operators have authority. Table C. 3 summarizes the main differences between the 2018 and 2023 grids in terms of conventional sources and provides the necessary information for the optimization step.

Table C. 3: Difference between 2018 and 2023 dispatchable sources in the Norman grid

Technology	**2018**			**2023**			**Cost of generation (€/MWh)**
	Installed capacity (MW)	**Lower generation limit (MWh)**	**Upper generation limit (MWh)**	**Installed capacity (MW)**	**Lower generation limit (MWh)**	**Upper generation limit (MWh)**	
Nuclear	10640	2036	9200	10640	2036	9200	12
Oil	127.8	15.634	124.862	35.8	4.379	34.977	30
Oil (combustion turbine only)	35.8	4.379	34.977				
Natural Gas	510.2	62.414	498.471	510.2	62.414	498.471	40
Coal	580	70.952	566.667	0	-	-	22.5

However, it is important to highlight the fact that costs are assumed here based on the historical and current situations and they might be subject to changes according to future markets.

- **Emission factors**

The ecoinvent processes for each technology available in the 2023 Norman grid are presented in Table C. 4 hereafter. We assume that there will be no major technological change over the short-term (5 years).

Table C. 4: ecoinvent processes for the different power sources in the 2023 Norman grid

Source	ecoinvent processes
Oil	electricity production, oil | electricity, high voltage | Cutoff, U – FR
	heat and power co-generation, oil | electricity, high voltage | Cutoff, U - FR
Gas	electricity production, natural gas, combined cycle power plant | electricity, high voltage | Cutoff, U – FR
	electricity production, natural gas, conventional power plant | electricity, high voltage | Cutoff, U – FR
	heat and power co-generation, natural gas, conventional power plant, 100MW electrical | electricity, high voltage | Cutoff, U - FR
Nuclear	electricity production, nuclear, pressure water reactor | electricity, high voltage | Cutoff, U – FR
Wind	electricity production, wind, <1MW turbine, onshore | electricity, high voltage | Cutoff, U – FR
	electricity production, wind, >3MW turbine, onshore | electricity, high voltage | Cutoff, U – FR
	electricity production, wind, 1-3MW turbine, onshore | electricity, high voltage | Cutoff, U – FR
	electricity production, wind, 1-3MW turbine, offshore | electricity, high voltage | Cutoff, U – FR

Solar	electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted | electricity, low voltage | Cutoff, U
	electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted | electricity, low voltage | Cutoff, U
	electricity production, photovoltaic, 570kWp open ground installation, multi-Si | electricity, low voltage | Cutoff, U FR
Hydro	electricity production, hydro, run-of-river | electricity, high voltage | Cutoff, U – FR
Bio	heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014 | electricity, high voltage | Cutoff, U - FR
	heat and power co-generation, biogas, gas engine | electricity, high voltage | Cutoff, U – FR

In 2023, **coal power sources** will be completely decommissioned; hence, they will be excluded.

Despite being available in France, some technologies are missing from the Norman grid; hence, they were not considered. Among the hydropower sources, only Run-of-River is available in Normandy; therefore, it was the only technology of hydropower taken into account.

In order to have a more holistic understanding of the effect of energy targets, the grid is also analyzed at the four endpoint categories. The corresponding EFs per category for each power source are listed in Table C. 5 below.

Table C. 5: EFs at the four endpoint categories for the different power sources

Technology	EF CC (tCO_2-eq/MWh)	EF HH (DALY/MWh)	EF EQ (PDF*m2*yr/MWh)	EF R (GJ primary/MWh)
Oil	0.9069	122.5573	8.88E-04	14.0373
Coal	0.9597	443.5578	5.98E-04	12.8720
NG	0.6193	12.5828	8.51E-05	12.0449
Nuclear	0.0120	59.3715	1.06E-04	14.1175
Wind	0.0141	9.0595	2.48E-05	0.2134

Solar	0.0833	52.7340	1.43E-04	1.1638
Hydro	0.0042	1.4221	7.15E-06	0.0440
Bio	0.0554	616.2307	6.58E-04	0.5513
Thermal	0.8116	229.3482	4.13E-04	12.6478

- **Energy storage system sizing**

The sizing of the ESS is outside of the scope of this paper. Therefore, the 700 MW of Li-ion batteries was based on (Elzein et al., 2018). For the year 2017, there were 500 MW of Li-ion batteries installed in the grid when the total installed capacities of all the power sources were 13 093 MW. The ESS represented 3.82% of that total capacity.

The total installed capacities for the Norman 2023 grid is: 18 269 MW ➔ 2023 ESS capacity is = $0.0382 \times 18\,269 = 697.88\ MW$

The considered size of batteries for the 2023 grid (scenario 3) is therefore: 700 MW

- **Carbon tax calculation**

The French government sets Carbon taxes (MTES).

The historical 2017 value for the Carbon tax was set at 30.5 €/tCO_2-eq. The goal for 2030 is set at 100 €/tCO_2-eq. Therefore, the cost for 2023 is obtained by linear interpolation.

Year	Cost of Carbon emission (€/tCO_2-eq)
2017	30.5
2023	X
2030	100

The cost of emissions for 2023 = 62.58 €/tCO_2-eq.

APPENDIX D SUPPLEMENTARY MATERIAL PUBLISHED WITH CHAPTER 7 (B)

Optimization equations

The optimized-consequential LCA approach which we relied on in this manuscript was based on the method developed in (Elzein, Dandres, Levasseur, & Samson, 2019). Therefore, we adopted the same optimization objective and equations.

The aim of the objective function is to minimize the **total cost** which includes the costs of fuel, electricity trade, GHG emissions, and generating unit start-up and shutdown. The optimization problem, therefore, results in an optimal electricity generation pattern with the lowest cost.

The optimization function is presented by the equation hereafter:

$$\text{Min } f(\text{X}) = \sum_{t=1}^{T} Cost^{t}$$

$$= \sum_{t=1}^{T}\{ \sum_{i=1}^{N_g}[\frac{u_{Gi}(t)P_{Gi}(t)GC_{Gi}(t)}{(t)-(t-1)} + u_{Gi}(t)P_{Gi}(t)EF_{Gi}(t)CC]$$

$$+ \sum_{j=1}^{N_s}[\frac{u_{Sj}(t)P_{Sj}(t)GC_{Sj}(t)}{(t)-(t-1)} + u_{Sj}(t)P_{Sj}(t)EF_{Sj}(t)CC]$$

$$+ [\frac{P_{Grid}(t)GC_{Grid}(t)}{(t)-(t-1)} + P_{Grid}(t)EF_{Grid}(t)CC]\}$$

Where:

- Generators are denoted by the letter G, and S designates storage systems.
- $u_{Gi}(t)$ and $u_{Sj}(t)$: status of unit i/j at time t, either 1 if the unit is on or 0 if it is off
- P_{Gi} and P_{Sj} *:* the active power of the ith generator and jth storage device at time t in (MW)
- GC_{Gi} and GC_{Sj}: generation costs of the ith generator and jth storage device at time t in (€/MWh)
- P_{Grid} *:* the active power which is bought/sold from/to the utility at time t (representing the trade) in (MW)
- GC_{Grid}: the average generation cost of the utility at time t in (€/MWh)
- $EF_{Gi}(t) = CO_{2_{DG_i}}$: Emission factor of CO_2 emissions from the ith distributed generator (DG) at time t expressed in (tCO_2/MWh)
- $EF_{Sj}(t) = CO_{2_{Storage_i}}$: Emission factor of CO_2 emissions from the jth storage at time t expressed in (tCO_2/MWh)

- $EF_{Grid}(t) = CO_{2_{grid}}$: Emission factor of CO_2 emissions from the utility at time t expressed in (tCO_2/MWh)
- CC: Carbon Cost expressed in (€/tCO_2)
- T: Total number of hours
- N_g: Total number of generators
- N_s: Total number of storage systems

The forecasted electricity generation from RES is on the 30-minutes basis and therefore, this is the optimization period considered. The consumers' demand is first supplied by the RESs, then by batteries (if charged) and finally by means of the dispatchable technologies.

The specifications of the power sources available in the 2023 Norman power grid are based on the French government reports and communications (Courtel et al., 2018; EDF, 2019; METS, 2016; PowerTechnology, 2019; WNN, November 2018). Their corresponding emission factors are estimated by means of OpenLCA software, econinvent database and Impact2002+ impact assessment method.

In this paper, the value attributed to EF_{Sj} is 0 because lithium-ion batteries (which are the ESS considered) do not have a cost or emit CO_2 when operated. We avoided double-counting by attributing the costs of generation and emissions to the power sources charging the battery and not the battery itself.

Three main conditions constrain the optimization problem:

- **<u>Constraint 1:</u> power balance**

To ensure stable operation of the grid, equality between the electricity produced and consumed must be maintained.

$$\text{Supply} = \text{Demand}$$

$$\sum_{i=1}^{N_g} P_{Gi}(t) + \sum_{j=1}^{N_s} P_{Sj}(t) + P_{Grid}(t) = \sum_{k=1}^{N_k} P_{Lk}(t)$$

Where P_{Lk} : the amount of kth load level (MW)

- **<u>Constraint 2:</u> active power limits**

Power plants have generation capacities and they can only deliver electricity within their allowable minimum and maximum limits.

$$P_{Gi,min}(t) \leq P_{Gi}(t) \leq P_{Gi,max}(t)$$
$$P_{Sj,min}(t) \leq P_{Sj}(t) \leq P_{Sj,max}(t)$$
$$P_{Grid,min}(t) \leq P_{Grid}(t) \leq P_{Grid,max}(t)$$

Where:

- $P_{Gi,min}(t)$ & $P_{Gi,max}(t)$: the minimum active power and the maximum power generation of the ith DG (MW)
- $P_{Si,min}(t)$& $P_{Si,max}(t)$: the minimum active power and the maximum power generation of the jth storage (MW)
- $P_{Grid,min}(t)$ & $P_{Grid,max}(t)$: the minimum active power and the maximum power generation of the utility (MW)

- **<u>Constraint 3:</u> battery limits**

Batteries also have capacities and can only store a specific amount of electricity. They cannot be charged or depleted over their limits.

$$W_{ess,t} = W_{ess,t-1} + \eta_{charge} P_{charge}(\Delta t) - \frac{1}{\eta_{discharge}} P_{discharge}(\Delta t)$$
$$W_{ess,min} \leq W_{ess,t} \leq W_{ess,max}$$
$$P_{charge,t} \leq P_{charge,max}$$
$$P_{discharge,t} \leq P_{discharge,max}$$

Where:

- $W_{ess,t}$ & $W_{ess,t-1}$: the amount of energy stored inside the battery (MWh)
- $\eta_{charge}(\eta_{discharge})$: efficiency of the battery during charge (discharge) process (%)
- $P_{charge}(P_{discharge})$: the permitted rate of charge (discharge) during the period of time Δt (MWh)
- $W_{ess,min}$ & $W_{ess,max}$: the lower and upper limits on the amount of energy storage inside the battery (MWh)
- $P_{charge,max}$ ($P_{discharge,max}$): the maximum rate of battery charge (discharge) (MWh)

APPENDIX E OTHER CONTRIBUTIONS

In addition to the three journal articles, this project was presented at national and international conferences:

- H. Elzein, T. Dandres, A. Levasseur, and R. Samson, "Short-term LCA of prospective grids," presented at LCA XIX, Tucson, AZ, USA, 2019.
- H. Elzein, T. Dandres, A. Levasseur, and R. Samson, "An Optimized LCA approach to evaluate prospective grids," presented at SAM13, Pisa, Italy, 2019.
- H. Elzein, T. Dandres, A. Levasseur, and R. Samson, "Investigating energy storage systems use phase " presented at SAM12, Metz, France, 2018.
- H. Elzein, T. Dandres, A. Levasseur, and R. Samson, "Assessment of the energy storage system use phase by means of an optimized consequential life cycle assessment methodology," presented at LCA XVII, Portsmouth, NH, USA, 2017.
- H. Elzein, T. Dandres, A. Levasseur, and R. Samson, "Combining optimization and consequential life cycle assessment to investigate energy storage systems," presented at the McGill-Ecole Polytechnique de Montreal Chemical Engineering research day, Montreal, QC, Canada, 2017.
- H. Elzein, T. Dandres, A. Levasseur, and R. Samson, "Optimized-consequential life cycle assessment methodology: a new approach for time-dependent systems investigation," presented at CYCLE 2016, Montreal, QC, Canada, 2016.
- H. Elzein, T. Dandres, A. Levasseur, and R. Samson, "Development of an optimized-consequential Life Cycle Assessment method: Application to the electricity generation sector," presented at the McGill-Ecole Polytechnique de Montreal Chemical Engineering research day, Montreal, QC, Canada, 2016.
- H. Elzein, T. Dandres, A. Levasseur, and R. Samson, "Development Of An Optimized-Consequential Life Cycle Assessment Methodology And Its Application To The Electricity Generation Sector," presented at LCA XVI, Charleston, SC, USA, 2016.