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Review

Sustainable Power Grid Expansion: Life Cycle Assessment, Modeling Approaches, Challenges, and Opportunities

Dahlia Byles and Salman Mohagheghi *

Electrical Engineering Department, Colorado School of Mines, Golden, CO 80401, USA; drbyles@mines.edu
* Correspondence: smohaghe@mines.edu

Abstract: Electric demand is steadily increasing, hence requiring continuous investments in modernizing, and expanding power grids worldwide. Traditionally, power system planning projects have considered minimizing the costs of capacity expansion and minimizing the amount of energy not served as the main objectives. With climate change policies enforcing the decommissioning of fossil-fuel-based generation, new clean and renewable generation technologies are being considered for power system capacity expansion projects. However, the environmental impacts of energy resources are not limited to carbon emissions and their contribution to global warming. In fact, every power generation technology can result in undesired impacts during its entire life cycle, which could negatively affect air quality, water resources, material resources, and/or human health. This paper provides an overview of how to assess the sustainability of power systems and power generation technologies based on life cycle assessment (LCA). A review of LCA, as applied to power systems and generation technologies, is presented with a discussion of general findings, challenges, and limitations. A review of the literature is then provided related to how sustainability objectives are currently incorporated in power grid design and capacity expansion models. Finally, shortcomings of the current models are discussed, along with opportunities for future research.

Keywords: capacity expansion planning; generation planning; greenhouse gas emissions; life cycle assessment; power grid; power system planning; transmission planning; sustainability

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1. Introduction

The U.S. Energy Information Administration (EIA) projects that, assuming no significant changes in policy or technology, world energy consumption will grow by nearly 50% between 2020 and 2050 [1], attributed mainly to global population and economic growth. Increased deployment of electrification projects in developing countries and a general demand for higher quality of life are key contributors, particularly energy demand for space cooling, which, absent policy interventions, is expected to triple by 2050 [2]. Other trends, such as electrification of the transportation fleet, are expected to shift energy consumption from primary fuels to electricity. It is estimated that by 2030, electric vehicles (EVs) in the U.S. will account for 4% of total final electricity consumption under the Sustainable Development Scenario [3]. Being able to respond to this increase in demand requires investment in modernizing power grids and expanding their generation and transmission capacities.

In the most general sense, power grid capacity expansion can be formulated as an optimization model that tries to find the lowest cost solution to meet the expected electric demand over a long-term forecast horizon of typically 10–20 years. When it comes to devising generation capacity expansion, decision variables of the model may include additional generation capacity to be added to a subset of existing power plants and new power plants to be constructed at a subset of candidate locations. Because the added generation capacity needs to be transmitted to demand areas, often there is a need to construct new transmission lines or expand the capacities of the existing ones. Combining the two problems of generation and transmission expansion is beneficial because, when it comes to renewable energy resources, many times, the energy resource is available at a location from which proper connections to the main grid may not be available.

Traditionally, the objective functions of the optimization model have included terms for deployment and operation costs to be minimized, energy not served to be minimized, or social welfare, often defined as the difference between the demand profile and production profile, to be minimized. Not surprisingly, the cost of grid expansion, which could include the cost of investment, operation, and maintenance, is the most important objective function considered [4–20]. In [11,20], an objective function was defined related to the salvage value of the installed resources at the end of the planning horizon to be maximized. Demand response, defined as voluntary demand curtailment targeting residential, commercial, and/or the industrial sector, can also be considered as virtual generation, in which case the costs associated with it need to be accounted for [11]. Authors in [17] also considered the cost of the worst-case imbalance between load and generation. Some have also included a cost term associated with involuntary load shed due to discrepancies between demand and generation, to be minimized [7,9,13,15]. In addition to the cost of generation and transmission enhancement, costs associated with repairs due to natural disasters can also be modeled [21]. Because the ultimate goal of grid capacity expansion planning is to ensure that demand is met, improvement in system reliability, for instance, in the form of minimizing the interrupted load and/or energy not served, can also be considered as an objective [5,11,12]. Other constraints have been considered, for instance, authors in [5] modeled the absorption of private investment for transmission lines as one of their objective functions to be maximized.

The optimization model above is subject to a variety of budgetary and operational constraints. The most common constraints that have been considered in the literature are the overall load balance, power balance equations at individual buses, power flow equations, line flow limits, and limits on generation capacity [4–7,9,11–17,20]. Other constraints may include limits on the investment budget [4,14,16], commissioning time and installation constraints [11,19], fuel demand [4,6,16], and fuel transportation [16]. Moreover, authors in [6] included a constraint to ensure that no islanding occurs during normal or contingency operations. This impacts the numbers and locations of new transmission lines to be installed. Conversely, authors in [9] allowed for islanding formation by recommending the deployment of black start capable units such as battery energy storage systems.

The changing climate and the rise in the frequency and severity of extreme weather events have created a consensus among the scientific community that materials and energy resources must be used in a sustainable fashion with minimal environmental impacts. In 2015, nations around the world signed the Paris Agreement pledging to combat climate change. To meet the strict goals developed in the agreement, many countries have begun transitioning their electric generation resources and grids away from fossil fuel-based technologies and instead, adopting clean and renewable energy generation alternatives such as hydropower, wind, or solar generation. With the pressure to decrease carbon emissions, many appliances and systems are being converted to utilize electricity as their primary energy source, e.g., EVs and electric heating. This trend is expected to continue, increasing the burden on electricity networks.

The United Nation's 7th sustainable development goal (SDG) is to ensure access to "affordable, reliable, sustainable, and modern energy", worldwide [22]. To meet this goal, the implementation of renewable generation and energy-efficient systems is expected to increase. Furthermore, the goal calls for sustainable electrification of underdeveloped and unelectrified areas. With the decommissioning of carbon-based generation, the increased electrification of systems, and the expansion of access to electricity, reliance on electricity is going to increase greatly beyond what is standard for population growth in the years to come. Renewable and clean energy generation is going to have to provide a significant portion of electric demand to consumers. However, the environmental impacts of energy resources are not limited to carbon emissions and their contribution to global warming. In fact, every power generation technology can result in several undesired impacts during its entire life cycle, which could negatively affect air quality, water resources, material resources, and/or human health. As power networks worldwide are expanded to accommodate the rise in demand, the sustainability of these projects must be assessed in a comprehensive and fair fashion and their negative impacts minimized. This is the only way to ensure that the autonomy of future generations is not sacrificed by our actions today.

This paper provides an overview of how to model power grid capacity expansion while considering sustainability. The most important tool to assess the environmental impacts of generation technologies is life cycle assessment (LCA), which models the footprint of those technologies over their entire life cycle. A review of LCA, as applied to power systems and generation technologies, is presented with a discussion of general findings, challenges, and some limitations. A review of the literature is then provided related to how sustainability objectives are currently incorporated in power grid design and capacity expansion. Then, shortcomings of the current models are discussed, along with opportunities for future research.

2. Modeling Sustainability through LCA

LCA is a sustainability modeling tool that quantifies the environmental impacts of a product or service over the course of its lifetime. It evaluates the environmental footprint by considering the inputs acquired from nature (e.g., material, energy, water) and the outputs to nature (e.g., waste, emissions to soil/water/air, etc.). LCA is meant to be utilized during the design and development of a product or service to identify environmentally harmful materials, processes, or activities associated with that product or service [23]. After the identification of environmental harms, developers and engineers can consider alternate methods of design to ensure minimal impact on the environment. Alternatively, LCA can be used to compare two or more products in terms of their environmental footprints. Here, it is essential to define a functional unit to be used as the basis of comparison.

The international standards organization (ISO) series 14,040 defines and outlines the four phases of life cycle assessment [23], which include goal and scope definition, inventory analysis, impact assessment, and interpretation. To clearly define the goal and scope of the assessment, the product system must be defined, the system boundary developed, and data categories chosen. Some LCA studies are reported as cradle-to-gate, which means that they only include impacts up to the point where the product is pushed out of the gate of the factory and do not consider negative effects that may arise from the product's use or disposal. Other studies may focus on cradle-to-grave, which offers a comprehensive assessment of the impacts during manufacturing and production (upstream), operation, and disposal (downstream) of the product (see Figure 1). Alternatively, an LCA study may only investigate the impacts associated with one process within the chain of production and use—an approach known as gate-to-gate.

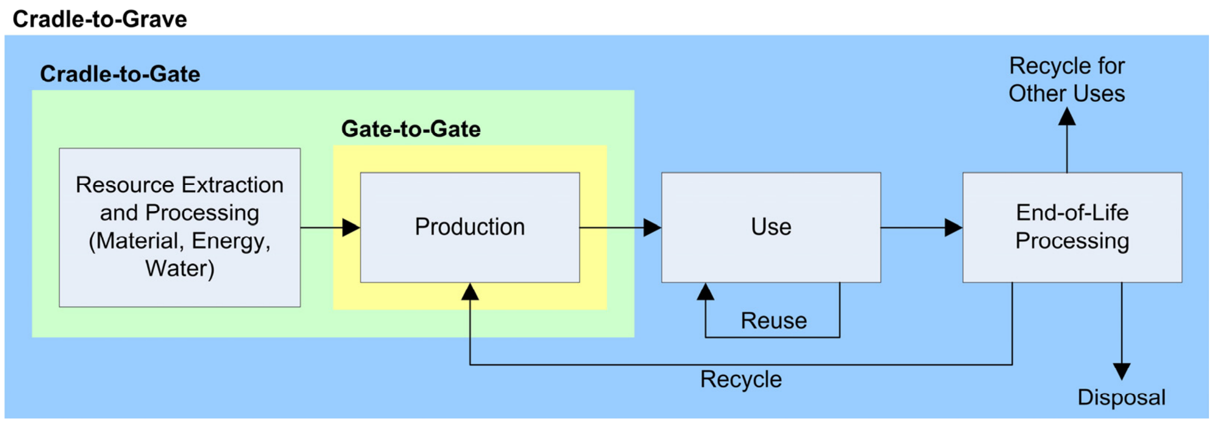

Figure 1. LCA boundaries.

Inventory analysis is the section that calculates the amount of output materials or processes related to the inputs to the system through a unit process. Impact assessment evaluates the findings from the inventory analysis phase. The results are classified into *midpoint impact categories* that may include acidification, freshwater eutrophication, ozone depletion, global warming potential, particulate matter, freshwater toxicity, land use, and mineral and fossil resources. These categories are then associated with *endpoint impact categories* of damage to ecosystems, damage to human health, and damage to resource availability (see Figure 2). The findings from LCA can be normalized or weighted depending on the scope of the study. Results can then be interpreted. An important aspect of interpretation of the results is an analysis of inconsistencies and key issues and limitations within data [23].

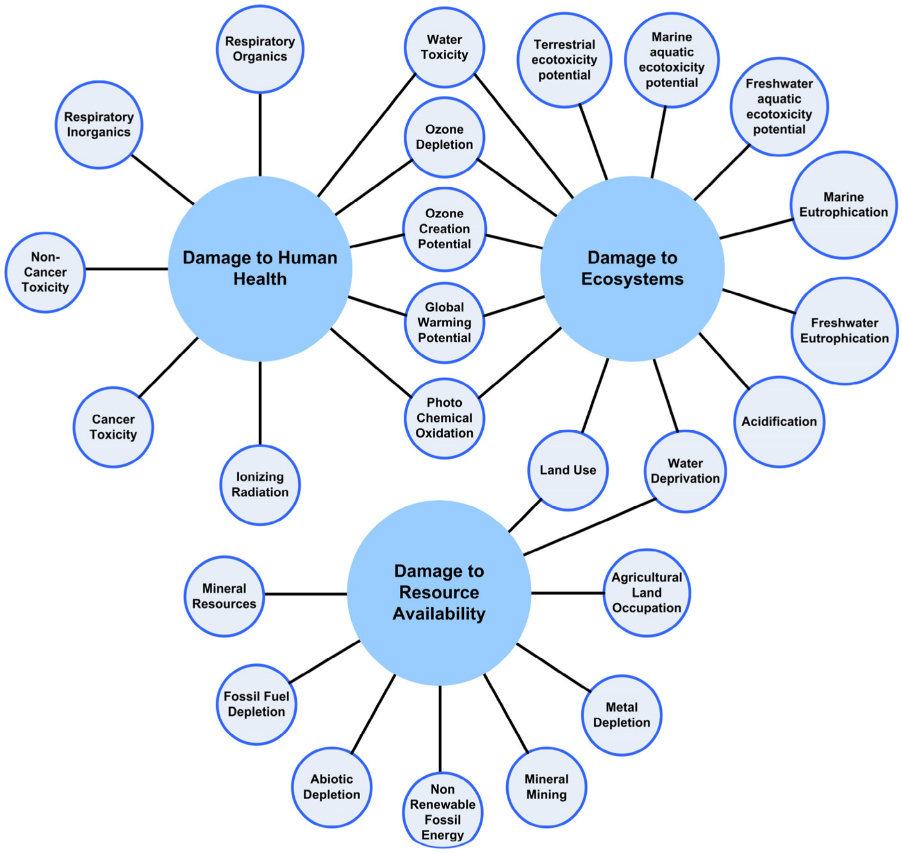

Figure 2. Common midpoint and endpoint impact categories considered in LCA studies. Not all categories are included in all LCA studies. Moreover, some studies define new categories, which may be a combination of one or more categories listed above.

LCA can be *process-based*, which uses inventory data for individual processes to methodically analyze material and energy flows at every stage of the life cycle, or *economic input-output-based* (EIO), which uses economic data to assess impacts, for instance, identifying the level of emissions for $1M of sales in a particular industry [24]. Generally speaking, process-based LCA is more appropriate for simpler and contained systems and studies, whereas EIO LCA is more suited for complex systems in which detailed environmental data about different processes may not be available with a high level of accuracy. A hybrid approach is also possible, where we start with one model as the baseline and then fill the gaps with the second model to refine the analysis.

LCA can also be categorized as *attributional* or *consequential*. Attributional LCA (ALCA) uses current and historical data that is measurable/known to model the impacts and assumes that changes within the LCA system do not impact the overall techno-sphere [24]. It models the system based on how things are and does not consider the effects of outside systems and policies on the system under study. Consequential LCA (CLCA), on the other hand, models the environmental impacts that might occur in the future in response to changes in technology, policy, or market. It performs a what-if analysis of the consequences of changes in the way a product is produced, used, and/or disposed of. CLCA analyses are more appropriate for large-scale studies.

Table 1 provides an overview of common tools for conducting LCA, along with their main characteristics.

Table 1. Overview of common tools for performing LCA, listed in alphabetical order. Acronyms used for midpoint impact indicators: AB: Abiotic resource depletion, AC: acidification potential (marine and/or freshwater), ACE: Acidification and eutrophication, AEC: Aquatic ecotoxicity, AS: Abiotic stock resources, CR: Carcinogenic potential, EA: Emissions into air, EC: Ecotoxicity potential, EGW: Emissions into groundwater, EQ: Ecosystem quality, ES: Emissions into soil (or topsoil), ESW: Emissions into surface water, ET: Eutrophication potential, ETF: Eutrophication aquatic freshwater, ETL: Eutrophication terrestrial, ETM: Eutrophication aquatic marine, EW: Emissions into water, FAE: Freshwater aquatic ecotoxicity, FD: Fossil fuel depletion, FET: Freshwater eutrophication, FEW: Freshwater ecotoxicity, FR: Fossil resources, FSE: Freshwater sediment ecotoxicity, GW: Global warming potential (climate change potential), HH: Human health impacts, HT: Human toxicity, HTC: Human toxicity cancerous, HTNC: Human toxicity non-cancerous, IR: Ionizing radiation, IRE: Ionizing radiations ecosystem quality, IRH: Ionizing radiations human health, LT: Land transformation, LU: Land use (occupation), LUT: Land use or transformation, MA: Malodorous air, MAE: Marine aquatic ecotoxicity, ME: Marine ecotoxicity, MET: Marine eutrophication, MEX: Material extraction, MR: Mineral resources, MSE: Marine sediment ecotoxicity, NRE: Non-renewable energy, OD: (Stratosphere) ozone layer depletion, PM: Particulate matter formation, PO: Photochemical oxidization, RE: Respiratory effects, RES: Resource use, RESE: Resource use for energy carriers, RESM: Resource use for minerals and metals (or natural resources), SF: Smog formation, TA: Terrestrial acidification, TAN: Terrestrial acidification and nutrification, TE: Terrestrial ecotoxicity, TOF: Tropospheric ozone formation, WA: Water availability, WST: Deposited waste, WT: Water turbined, WTP: Thermally polluted water, WU: Water use, WW: Water withdrawal. Note that there may be partial overlaps among some of the indicators listed above, which is due to the different modeling approaches and terminology adopted by various LCA tools.

Methodology	Midpoint Impact Indicators Used	Features	Reference
CED	direct and indirect energy usage throughout the entire life cycle of a system in megajoules (MJ) broken into renewable and non-renewable resources	Considers many types of energy sources.	[25]
CML	AC, ET, FAE, FSE, GW, HT, IR, LU, MA, MAE, MSE, OD, PO, RES, TE	Developed based on European conditions and systems.	[25]
Eco-indicator 99	ACE, CR, EC, FR, GW, IR, LU, OD, RE, RESM	Has the same endpoint categories as ReCiPe and various perspectives.	[25]
Ecological Scarcity Method 2006	EA, EGW, ES, ESW, WST, RESE, RESM	All impact categories fall under one impact category group of depletion of abiotic resources.	[25]
EF	AC, ET, GW, HTC, HTNC, IR, OD, PM, PO, ETF, ETL, ETM, FAE, LU, WU, RESE, RESM	Derived from ILCD.	[26]
EPS (Environmental Priority Strategies) 2000	AS, EA, ES, EW, LO	Assesses the economic damage related to emissions and use of energy, materials, and land.	[27]
ILCD 2001	AB, AC, EC, ET, GW, HT, IR, LU, OD, PM, PO	Has three areas of protection: Human health, resource depletion, and ecosystems.	[25]

Table 1. *Cont.*

Methodology	Midpoint Impact Indicators Used	Features	Reference
Impact 2002+	AC, AEC, ET, GW, HT, IR, LU, MEX, NRE, OD, PO, RE, TE, TAN, WT, WU, WW	Takes each midpoint impact indicator to an endpoint category, which includes human health, ecosystem quality, climate change, and resources.	[28]
Impact World +	AC, EQ, FAE, FET, HH, HTC, HTNC, IRE, IRH, LT, LU, MET, OD, PM, PO, TA, WA, WTP	Long term considerations with a variety of granular resolutions.	[29]
IPCC	GW	Considers only GHG emissions.	[27]
ReCiPe	FET, FEW, FR, GW, HTC, HTNC, LUT, ME, MET, MR, OD, PM, TA, TE, TOF, WU	Utilizes three different perspectives that represent different timescales. Has been iteratively developed with CML and Eco-indicator as its predecessors. Considers worldwide impacts. Does not include potential impacts for future extraction.	[30]
Traci	EC, ET, FD, HH, OD, SF	Developed based on the United States regions.	[31]
USEtox	Various exposure and effect parameters	Specifically designed for chemicals.	[32]

3. LCA for Power Systems

When it comes to the design and operation of the power grid, no technology is free from negative impacts. While operation of some generation technologies, such as fossil fuels, are well known to cause a myriad of severe environmental consequences, renewable power generation technologies can also lead to negative impacts, albeit at smaller scales and often localized. However, for most renewable technologies, the majority of negative impacts occur during the construction stage and/or recycling stage, e.g., particulate matter and/or greenhouse gas emissions during the production of solar photovoltaics (PV) and wind turbines, toxic discharge in solar PV manufacturing, or possible greenhouse gas emissions during recycling of batteries and solar PV panels. Regardless, a move towards a green electric power grid necessitates a comprehensive and unbiased assessment of various technologies to ensure that the harms to the environment and society are minimal. This section presents a review of the LCA studies applied to power systems and provides a discussion of the general findings, challenges, and limitations associated with the state-of-the-art.

3.1. Case Studies

3.1.1. Impacts of Power Generation Technologies

Many researchers have conducted LCA studies to evaluate the environmental impacts of power generation technologies in different countries. The general goal of these studies is to provide an unbiased comparison between renewable and non-renewable generation technologies and to assess the impact of various green generation policies on the environment. For instance, authors in [33] performed ALCA of Portugal's electric grid from 2003 to 2012, with cradle-to-gate boundary, including generation, transmission, and distribution infrastructure. They found that hydropower had the lowest impact factor for each impact category, while oil-based and coal-based plants had the highest impacts in several categories. Although, the introduction of desulphurization and denitrification systems helped decrease the negative impacts of coal. During the study period, the environmental impacts decreased by more than 50%, which the authors attributed to the increased usage of hydropower, wind, and natural gas. A similar study was conducted in [34], with a focus on Mexico, which found that natural gas had lower environmental impacts in almost every impact category compared to coal, diesel, and heavy fuel oil. Further, combined cycle power plants with carbon capture technology showed better environmental performance only in the global warming potential (GWP) category, which the authors attributed to the lower efficiency of plants with carbon capture systems. For renewables, environmental impacts during the operation phase appeared to be dominated by the transmission of electricity. Similarly, an LCA for 31 different provinces of China [35] indicated coal power plants as having the highest environmental impacts, followed by solar, hydro, wind, and nuclear generation. The authors determined that the high environmental impacts of solar were due to its long supply chain. Similar conclusions about the environmental impacts of coal power plants were reported in [36–39]. A study of the power grid in the UK in [40] indicated that the phasing out of natural gas combined cycle and coal power plants can result in a 60% decrease in GWP.

However, renewable generation technologies can have negative consequences as well. For instance, in [40], the authors concluded that a rise in the deployment of offshore wind and lithium-ion batteries can lead to an increase in human toxicity potential, whereas those technologies, in addition to solar PV can result in higher abiotic depletion potential. The same conclusion was confirmed in [39] about solar PV. Others have concluded that the construction of wind and solar plants is more carbon-intensive than any other power plant [38]. Authors in [41] found that the usage of wood chips for cogeneration of heat and power had high environmental impacts in the agricultural land use category. In [40], the authors observed that biogas-fired electricity was a large contributor to GWP, even though it is considered a zero-carbon technology.

3.1.2. Temporal Variations of the Generation Mix

Modeling the dynamics and temporal variations of energy supply has an important impact on the results of the LCA. While a simplified analysis may consider an average mix of generation technologies for all demand levels, a detailed temporal analysis would instead model different hourly demands and the generation sources that supply each one based on the availability of energy resources. This leads to identifying the marginal generation technology, which is the resource that is most likely to respond to a change in demand. Renewable energy resources can further complicate this assessment due to their intermittent nature. So do dual-use resources, such as combined heat and power (CHP), whose electricity output would also be dependent on heat demand.

To show the impact of the generation mix on the results of LCA, a comparative study was conducted in [42] for five different sectors of U.S. economy (e.g., coal mining, semiconductor industry, automobiles, steel, and hotels) considering different generation mix scenarios, i.e., national average electricity mix, state mixes, state mixes including imports, and a sector-specific mix, and the results indicated that greenhouse gas emissions (GHG) for certain scenarios can change by more than 100%. In [43], the authors conducted a CLCA of the Danish power grid to determine the marginal generation technology and concluded that the constraints and fluctuations of real-life energy systems create a situation in which the de facto marginal source of electricity production is not coal or natural gas but a mixture of different technologies using different fuels. To assess the marginal generation technology, authors in [44] obtained generation mix data for each hour of the year. They used this data to identify the marginal generation sources by determining the variations in generation per technology between each hour of the hourly electricity mix. This data was then used in a CLCA. Authors in [45] conducted an LCA while considering the short-term dynamics of the electricity supply. They investigated grid-connected solar PV and small-scale wind turbines by looking into the marginal electricity production on an hourly basis. Their analysis indicated that a detailed short-term time horizon approach can lead to results that can be significantly different (up to 200% difference) from those obtained from simplified models, for instance, those considering an average supply mix. Similarly, authors in [46] compared GHG emissions using a national grid emission factor and hourly variations in grid emissions. An analysis of the electricity delivered to the Spanish grid in 2012 revealed that, for companies operating during the day, GHG emissions calculated in real-time were up to 9% higher than those calculated by the national grid emission factor, whereas, for companies operating during night hours, GHG emissions were up to 3% below those determined by the average method. Seasonal variations may have a significant impact on the results as well. For instance, in a study of Belgium's grid in [38], the authors concluded that the months of January and February had the highest average production of GHG due to the increased reliance on natural gas during those months. As another example, it was shown in [47] that domestic production in the Swiss power grid during summer months leads to the highest cumulative energy demand impacts, which reflect the energy intensity of power generation processes.

Determination of the marginal generation technology requires not just considering demand and weather variations but also market dynamics. Authors in [48] proposed a method to link an economic model with LCA in order to assess the intra-annual and long-term variations in the environmental impacts of the power grid in Hungary. The economic model considered the markets for gas and electricity to determine power production for each technology, power coming from neighboring countries for each technology, and power imported to neighboring countries. This information was then interpolated into hourly data and supplied to the LCA module. Their analysis indicated that intra-annual electricity composition does not have a major impact in the primarily fossil-fuel-based market. However, its significance increases with a higher penetration of renewable resources.

Considering temporal variations becomes especially important when analyzing energy storage systems due to their coupled time horizon of operation. For instance, a CLCA was conducted in [49] to assess the environmental impacts of lithium-ion batteries in a power system in France. To model the temporal operation of batteries, the authors developed an optimization model to minimize the cost of electricity and emissions (through a price on carbon). This information was then used to assess the environmental impacts of batteries compared to the base case (i.e., with no optimization), which indicated a more than 50% reduction in GHG emissions and a 28% reduction in marginal operating costs. The authors also compared the results with a non-temporal model with a high-level assumption that the power produced by energy storage would substitute 40% of the power coming from gas turbines. Their analysis showed that not considering the temporal aspects leads to the overestimation of the benefits gained by the deployment of storage systems.

3.1.3. Spatial Distribution of the Generation Mix

When it comes to determining the generation supply mix, in addition to temporal variations, it is important to model the spatial distribution of generation resources. Common techniques to do this are to model the emission factors based on generators within the territory of a single utility, within a State, within a North American Electric Reliability Corporation (NERC) region, or on a national scale, where each model ignores energy trades beyond the area under study, e.g., interstate for state scale or international for the national scale. Authors in [50] proposed a nested approach to calculate the emission factor as a weighted average of the emissions of local and regional generation sources. They used the trade between local and regional operators and utilities to determine the amount of electricity that comes from each generating pool and assigned a percentage of each pool's emissions to the final quantity of consumed electricity. The weights of the utility and NERC region generators were calculated based on the percentage of local versus imported electricity over a one-year period. They conducted a study for the U.S. primary aluminum industry and found that GHG emission factors using the nested approach increased the emissions contribution by up to 42%.

3.1.4. Electricity Import and Export

Another aspect of the generation supply mix that needs to be modeled is the electricity import and export. The source of power exchanged with outside systems can change both temporally and spatially and hence, can have a significant impact on the outcome of the LCA, for instance, when determining the marginal generation technology. In [47], the authors performed an LCA of the power grid in Switzerland, considering domestic production, electricity imports, and electricity exports on an hourly basis for a one-year period. The results of the study indicated that imports from Germany, with its large GHG footprint, make up 70% of all GHG emissions on the Swiss grid, which typically occur during the winter months. French and Austrian imports, on the other hand, had smaller impacts on the network. A similar conclusion was made in the study of Belgium's network in [41], where it was determined that importing electricity from the Netherlands under an ALCA model had a high environmental impact while importing from France may decrease overall impacts.

3.1.5. Material Consumption

While environmental impacts that arise from the operation of the power system are undoubtedly important, the rise in population, and consequently the electricity consumption, has led to the construction of more power plants and transmission and distribution circuits to supply the demand. Hence, the material and resource consumption associated with grid capacity expansion projects must be considered and has been the subject of many LCA studies. For instance, authors in [51] conducted a study of the impact of generation, transmission, and storage systems on bulk and critical materials such as steel, aluminum, and neodymium. Their results showed a rapid growth in demand for most materials in the electricity sector because of increased electricity demand and a shift towards renewable electricity technologies, which have higher material intensities and drive the expansion of transmission infrastructure and electricity storage capacity. They concluded that for neodymium, the annual demand grows by a factor of 4.4, whereas global demand for steel and aluminum in the electricity sector grows by a factor of 2 in the baseline or 2.6 in the 2-degree climate policy scenario. The authors also noted that climate policies that demand higher annual energy efficiency may lead to a lower installed capacity of generation technologies, which leads to less material usage. Authors in [52] conducted a hybrid LCA analysis for an offshore wind farm, focusing on cables, high voltage direct current (HVDC) links, and substations, with the functional unit defined as 1 kWh of electricity transmitted. Their analysis indicated that the HVDC cable was the largest contributor for all impact categories, causing nearly half of the total climate change effects and roughly 60% of all other impact types (e.g., toxic effects in humans and ecosystems). Authors in [53] conducted an LCA to study the environmental impacts of proposed transmission network capacity expansion projects to accommodate renewable energy integration across the EU. The system boundary consisted of the transmission network, and the authors considered overhead lines, land/subsea cables, and substation equipment. For building new lines, they concluded that manufacturing leads to the most significant negative impacts. When it comes to upgrading the existing lines, they found that voltage upgrades lead to the highest environmental impacts, followed by line reconductoring, decommissioning, or reinsulating to a higher voltage level.

3.1.6. Power Losses

In addition to the upstream material consumption, power losses have been shown to be one of the most significant contributors to the environmental impact of the transmission network. An LCA of Britain's transmission network was performed in [54] at voltage levels of 132–400 kV, using a cradle-to-grave boundary. The study considered overhead lines, underground cables, substation switchgear, and transformers and found that transmission losses had the largest energy and CO_2 impacts. The authors concluded that underground cables could help with reduced emissions due to lower losses and made the case for investing in low-loss but high-capital transmission line technologies. In [55], the authors conducted an LCA for power transmission and distribution in Norway. They modeled impacts associated with the production, transportation, and installation of components, as well as power grid losses and losses of SF_6. Their analysis showed that distribution, regional transmission, and national transmission networks in Norway account for 60%, 20%, and 20% of the total carbon footprint, respectively. These impacts were less than those of power generation but nonnegligible regardless. Further, power losses, which were modeled considering the energy mix in Norway, were found in their study to be responsible for 30–43% of the combined impact potentials for climate change, particulate matter, smog creation, and acidification, 21–28% for toxicity and eutrophication, and 14% for metal depletion. In a similar study, the authors in [56] conducted an LCA to assess the impacts of overhead, underground, and subsea transmission lines. They adopted a process-based LCA and assumed the European power mix to assess power losses in the equipment. Results of their study indicated that under the assumption of the European power mix, power losses are the dominant source in all impact categories, with the only exception being the category of metal depletion, for which the production of metal parts was the most relevant source. Related to the infrastructure, materials for masts and conductors were dominant for overhead lines. Concrete foundation was third in the impact category, with installation activities (transportation, construction, excavation, etc.) having a small share of total impacts. For cables (land and subsea), material production (copper, lead, and steel for armoring subsea cables) was the dominant source of impact. For land cables, trace (i.e., removal of asphalt and building a new layer of sand, cement, and asphalt) and, particularly, production of asphalt had a significant impact. Interestingly, end-of-life processing led to costs rather than benefits for land cables. One process which was found to have a high impact was the treatment of oil-impregnated paper, which should be incinerated. This was not the case for subsea cables, where recycling showed benefits in the categories of metal depletion, human toxicity, particulate matter formation, fossil depletion, and climate change. Similarly, an LCA of Norway's transmission grid presented in [57] listed raw material extraction and power losses to be the top two sources of climate change potential. Lastly, an analysis was presented in [58] to assess the GHG emissions from transmission losses. To account for both energy consumption as well as the burden on the transmission network, the authors introduced the concept of energy distance for each consumer, defined as the sum of the amount of electricity consumed multiplied by the transmission distance from each source. They conducted this study for the Chilean power grid and argued the importance of losses to be considered alongside consumption.

3.1.7. Power Distribution Systems

Several studies have focused on the environmental impacts of distribution networks. This is especially important as more distributed and renewable energy resources are being deployed at the medium voltage (MV) and low voltage (LV) levels. For instance, authors in [59] combined a CLCA with net energy analysis to assess the impacts of an increase in the deployment of distributed energy resources (DERs). They argued the need for considering temporal aspects to achieve a fair comparison between renewables and non-renewables. They considered the effects of DER penetration on the distribution grid (e.g., the need for reinforcing lines, upgrading transformers, and installing tap-changing transformers and other monitoring equipment) and on the overall grid (e.g., more power generated onsite, more intermittency, and changes in the utilization rate of other generators). In [60], an LCA study was presented to compare the environmental impacts of overhead lines against underground cables for MV distribution lines specific to the Southern California Edison territory and inventories. The functional unit was defined as the distribution of power in one circuit over one mile for one year. The authors concluded that for all impact category indicators, the worst case of the overhead system had lower impacts than the best case of the underground system. Further, for both systems and all impact categories, most of the impact occurs during cable production, in which aluminum production is the single largest contributor. The authors cited challenges with consequential system expansion, accounting for the impacts of cable recycling and energy recovery through byproduct combustion. The authors in [61] conducted an LCA of Denmark's distribution network (up to 50 kV), including transformers, cable ditches, poles, substations, switchgear, and circuit breakers. The most impactful life cycle process in their analysis was found to be the manufacturing of cables due to the heavy raw material usage. The recycling of materials at end-of-life was found to balance most life-cycle impacts. For cables, it was found that aluminum-based cables had lower impacts than copper-based ones. Cement usage in substations constituted a large amount of their impact. The impacts from the distribution network were then compared to the Danish transmission system, and it was found that the former had larger impacts due to higher losses and greater complexity.

There have also been studies conducted specifically on transformers and other substation equipment. For instance, an LCA was conducted in [62] assuming a European power mix, and the authors concluded that power losses were the most dominant source for almost all impact categories (contributing at least 96% to climate change impacts), with the only exception being the category of metal depletion, which was mainly impacted by the production of raw materials. For some equipment using SF_6, climate change impacts due to leakage surpassed those due to losses. Recycling showed benefits for most impact categories.

Table 2 provides a summary of some of the LCA studies applied to power systems in different countries. This is not a comprehensive list. However, it is intended to provide an overview of common scopes and features adopted in various LCA studies applied to power systems.

Table 2. Overview of the characteristics of LCA studies conducted on power systems of different countries. Acronyms used for the system: D: Distribution, G: Generation (may or may not consider the generation mix), T: Transmission, T&D: Transmission and distribution. Acronyms used for impact categories: AC: Acidification potential, AD: Abiotic depletion potential, AG: Agricultural land occupation, ET: Eutrophication potential, FAE: Freshwater aquatic ecotoxicity potential, FD: Fossil fuel depletion, GW: Global warming potential, HT: Human toxicity potential, MAE: Marine aquatic ecotoxicity potential, MD: Metal depletion, NRE: Non-renewable fossil energy, OC: Ozone creation potential, OD: Ozone layer depletion potential, PM: Particulate matter formation, PO: Photochemical oxidation, RD: Resource depletion, RE: Respiratory disorder, RM: Radioactive materials, SW: Solid waste, TE: Terrestrial ecotoxicity potential, WD: Water deprivation (scarcity) footprint, WT: Water toxicity. When the boundary is not specified by the authors: Gate-to-gate is used to denote studies in which the power grid infrastructure and components are included but do not cover extraction, transport, and processing of raw material/fuel or analysis of end-of-life recycling and waste disposal. On the other hand, cradle-to-gate is assigned to studies in which the extraction, transportation, and/or processing of materials and fuels are taken into account.

Ref.	Country	System	Impact Categories Considered	Boundary	Approach	Data Sources	Modeling Assumptions
[33]	Portugal	G, T&D with power losses	AC, AD, ET, GW, NRE, OD, PO	Cradle-to-Gate	ALCA	Reports from Energy Services Regulatory Authority	Grid was built at one time and has a lifespan of 40 years.
[34]	Mexico	G	AC, AD, ET, GW, OC, OD, HT, FAE, MAE, TE	Cradle-to-Gate	N/A	Ecoinvent database	Wind generation, oil transport, and refinery, efficiency for combined cycle with carbon capture, and captured CO_2
[35]	China	G	GW	Cardle-to-Gate	Comparative Analysis	Published data used in LCI and SimaPRo 7.3 LCA	N/A
[36]	Indonesia	G, T losses	AC, AD, ET, GW, PO, ADP, WD	Cradle-to-Gate	ALCA	Primary and secondary data	N/A
[37]	South Korea	G, T&D losses	GW, PM, PO, RM, SW, WT	Cradle-to-Grave	ALCA	National average data from public databases and the literature	N/A
[38]	Belgium	Hourly G in 2011	GW	Different processes for each fuel	ALCA	Electrabel–GDF SUEZ, Ecoinvent, and national statistics	N/A

Table 2. *Cont.*

Ref.	Country	System	Impact Categories Considered	Boundary	Approach	Data Sources	Modeling Assumptions
[39]	Spain	G	AC, ET, FAE, GW, OD, PO, RD	Cradle-to-Grave	CLCA	Ecoinvent database	Various assumptions
[40]	UK	G	AC, AD, GW, HT, NRE	Cradle-to-Gate	CLCA	Ecoinvent database	N/A
[41]	Belgium	Low voltage G	AC, AG, GW, ET, FD, HT, MD, OD, PM, PO, WD	various geographical boundaries	ALCA and CLCA	Data available from European system operators	N/A
[47]	Switzerland	G	FD, GW	Cradle-to-Grave	ALCA	Central Europe Energy Exchange database	Some uncertainties introduced associated with countries neighboring Switzerland
[54]	Great Britain	T	CO_2, Energy sources used	Gate-to-Gate	ALCA	Variety of databases, mostly from National Grid and Scottish Power	N/A
[57]	Norway	T	AG, ET, GW, HT, MD, OD, PO, WD	Cradle-to-Grave	N/A	Variety of primary and secondary sources	N/A
[61]	Denmark	D	AC, FD, GW, HT, MD, TE	Gate-to-Gate	N/A	GaBi 4.4	Assumes all technologies are current with a lifetime of 40 years.
[63]	Poland	G	GW, NRE, RE, TE	Cradle-to-Gate	N/A	The Central Statistical Office of Poland	Some assumptions pertaining to data

3.2. General Findings

Every LCA study leads to slightly different findings and conclusions depending on its respective boundary system and adopted methodology. However, there are some general results that are relatively consistent throughout most studies. When it comes to generation technologies, it is apparent that renewables have a significantly decreased GWP impact. This is a clear indication as to why these resources should continue to be deployed as replacements for more carbon-intensive generation technologies such as coal and natural gas. Coal has consistently been found to be the most polluting technology [33–39], especially anthracite coal [37]. Natural gas plants have been found to be an effective interim solution to offset the emissions from coal [34]. Hydropower has also been shown to have the least amount of impact categories [33,35]. However, LCA studies do not normally consider the loss of biodiversity, which hydropower can greatly cause [34].

Most of the emissions associated with power generation can be caused during the operation phase (electricity production) or during the course of building the infrastructure and production and extraction of fuel. The latter, known as upstream emissions, is estimated to be around 20% of the total emissions for fossil fuel generation [64], but dominant for renewable-based technologies. In general, air emissions are higher during electricity production, whereas water emissions are more significant during upstream processes, especially in fossil fuel technologies. Emissions and land/water impacts associated with the production of fuel are remarkably high for bioenergy.

The main negative impacts of renewable generation technologies are material use and transmission losses. Construction of wind and solar PV is shown to be more material intense [51] and more carbon intense [38] than any other generation technology and can lead to significant abiotic depletion potential [39,40]. What makes the construction of solar PV especially challenging from an environmental perspective is its long supply chain [35]. In addition to direct material usage, wind and PV plants are normally constructed where the energy resource is abundant, which may be far away from the main transmission or distribution grid, hence, requiring the construction of additional overhead lines and/or underground cables themselves being energy and material hungry processes. Due to the material intensity (steel, copper, and aluminum) of high-voltage and high-capacity lines, the construction of this infrastructure contributes to metal depletion and freshwater eutrophication [53,56,61]. Although, lines that utilize aluminum may have lower impacts than copper [61]. Some LCA studies have also indicated the noticeably higher environmental impacts associated with underground cables, compared to those of overhead lines [60,61], in part due to the former being more materially intensive. In addition to resource requirements, power losses contribute significantly to the environmental impacts of transmission and distribution networks. Although, these losses are, in general, lower than those from generation resources. Distribution networks typically produce more emissions compared to transmission grids [54,61], which is attributed to their higher power losses. In general, investing in high-quality (low-loss) conductors may be a sound approach, given the long-term environmental benefits of reducing power losses. If additional substations and transformers are needed, their impacts need to be considered as well, especially for gas-insulated equipment utilizing SF_6, due to the potential leakage of this gas, which is one of the most potent GHGs [53,57,62].

Further, the intermittent nature of wind and solar resources necessitates the deployment of energy storage technologies, which in the case of battery systems, can lead to human toxicity and abiotic depletion potential impacts [40]. Energy efficiency techniques can be used in conjunction with the deployment of renewable energy technologies to offset part of the need for building new plants and/or transmission or distribution lines.

3.3. Challenges and Limitations

Findings from LCA studies must be judged based on the completeness of the analysis, especially when comparing different generation technologies or grid expansion policies. Not every LCA study considers all relevant processes and subsystems or all pertinent impact categories. For instance, many LCA reports only consider the effects of GHGs and no other life cycle impacts [38,47,58,65]. To ensure proper design and analysis of the power grid, the majority of impact categories should be considered, especially those representing contributions to resource depletion, human health, and ecosystem damage. As another example, many LCA studies model transmission and distribution (T&D) networks based only on power losses and not material usage [34,37,48,58] or only consider the transmission network and not the distribution network, despite the fact that most power losses come from the latter.

Another source of variability in conclusions is related to the difficulty in defining the proper system boundaries. This is more of an issue for process-based LCA and can be avoided by using the input-output LCA. However, the latter introduces a higher level of uncertainties due to major sources of error in the modeling methodology [66]. Hybrid methods can solve the problem by expanding the system boundaries while maintaining data specificity for key system processes [66]. In addition to the variabilities due to methodologies adopted, datasets used, and the geographical region studied, other key factors may result in variabilities among different LCA studies, for instance, capacity factor, operation lifetime, combustion efficiency, quality of the fuel, and end-of-life processing [67].

Availability and quality of data are major challenges that can lead to limitations on the boundary of the system to be studied. Process-based LCA models require more detailed data on various input and output flows of different subsystems, which may not be readily available or accessible to the public. Further, when it comes to cutting-edge technologies such as third-generation solar PV, latest battery chemistries, or carbon capture technologies, the available data may be outdated and not a true representative of the latest advances. Even when the data is available, it is often static, i.e., it is not able to consider the future improvements in the technologies, future cost reductions, or other policy changes that might impact the deployment and/or effectiveness of those technologies. Input-output LCA models, on the other hand, use high-level economic data to model systems. However, this solution comes at the expense of making simplifying assumptions and approximations, which may impact the validity of the results of the study.

Availability of the data aside, its quality also has a major bearing on the study's outcome. There may be significant uncertainties associated with the accuracy of the data, trustworthiness of the data source, validity of the underlying mathematical models, and/or the scenarios considered. The latter can inform how the growth in demand, the availability of the energy resource, the efficiency of the underlying technology, or policy mandates are incorporated into the model. Another relevant question related to the robustness of the LCA study is whether and how to model high impact low probability (HILP) scenarios that may affect the ability of some power plants to function.

The selection of attributional versus consequential LCA is another important decision to make. ALCA may fail to see the impacts of the system under study outside its boundary or, alternatively, the policies from the outside world that might affect the system's operation or production. For instance, suppose we perform an ALCA for a particular renewable energy system. This may ignore the impact this system might have on reducing the output of other polluting power plants nearby (or decommissioning them altogether). Similarly, if certain government incentives encourage the production of a renewable system over other polluting ones, those factors may not be considered. Another example arises when certain policies mandate the usage of a particular resource, e.g., natural gas coming from a particular region, rare earth metals not from a certain country, system elements domestically built instead of imported ones, etc. Another issue to consider is if two industrial sectors compete for a limited resource, for instance, the grid and liquid fuels industry both need biomass feedstock, hence, influencing future policies, technological developments, and resource allocation [66]. To decide between attributional versus consequential LCA, the authors in [68] proposed a criterion based on the relative economic size of the object under investigation and suggested using CLCA if the object accounts for a larger share of the economy. However, CLCA for the power grid is not easy unless the policies are clear, non-ambiguous, certain, and not expected to change. The often-complex relationships between a product and the wider system, including social and economic dynamics that are more challenging to model, mean that although a CLCA might be considered more comprehensive, there is greater uncertainty in it than in ALCA [59].

In addition to the system boundary and the impact of outside decisions, the choice of ALCA or CLCA can affect the generation mix considered for the study, which, in turn, affects the negative impacts of the operation of the electric grid. Different results will arise if an average mix is considered in calculations, for instance, as is the case in ALCA, or the marginal generation, as in CLCA. The average electricity mix is based on the assumption that electricity production and consumption remain constant through the period of time under study (which could be short-term or long-term). However, this assumption most often is not valid, as the mix changes during the year and from one year to another based on weather data, availability of water resources, variations in demand and consumption patterns, and changes in technologies. In particular, the annual energy mix masks the seasonal variations in generation and demand. Another factor that may affect this is the energy imports and exports to neighboring regions and countries, which may change due to financial, policy-related, or political factors. In a sense, ALCA can be viewed as calculating the GHG emissions of the average consumption at any point in time [64]. On the other hand, in CLCA, changes in generation or consumption can impact the marginal technology that produces electricity. In general, there are two types of marginal generation, i.e., short-term, which concerns the order with which generators come online to respond to the load, and long-term, which provides an estimate of the next generation facility likely to be built in a certain market given current economic, political, and resource constraints [69]. The short-term marginal generation is dependent on the location and time of the demand and can vary significantly during the course of the day or between seasons depending on consumption and weather patterns. Another factor that can change the short-term marginal technology is the availability of stored energy, e.g., reservoir hydropower [64].

Further, an increase or decrease in demand can lead to changes in the price of electricity, which may, in turn, impact the units that are more economical to respond to changes in demand. The authors in [64] also argue that an increase in CO_2 emissions leads to a rise in the price of emission allowances (which are defined and limited), which may mean that some other generators may need to compensate for it. Long-term marginal generation is more a function of demand growth, policy, resource constraints, etc. [69]. An increase in electricity consumption, evolution of the market, sociopolitical decisions, and decisions to retire old power plants may attract new power plant investments. Focusing on short-term marginal generation would mostly ignore the environmental consequences of baseload generation [69], which is often the most polluting one.

Impact allocation is another challenging aspect of LCA that needs to be addressed, especially in ALCA studies. This occurs when the power plant produces multiple products, e.g., power, heat, or fuel byproducts, to which different percentages of emissions need to be assigned. Further, how reactive power support is allocated is another challenge, especially due to its localized nature compared to active power.

4. Sustainable Power Grids: Capacity Expansion Models

To ensure sustainability in design and capacity expansion, some researchers have used the findings from LCA studies to inform, critique, and compare energy policies and decisions. For instance, authors in [40] analyzed the effectiveness of energy transition plans of UK's largest utility. Authors in [70] adopted a similar approach but compared proposed grid mixes in 2030 versus 2010. In [49], an LCA-based method was developed to help policymakers with deploying energy storage systems. In another study, authors in [71] developed an LCA-based methodology for determining carbon tax incentives that only considered environmental impacts and not cost. Lastly, LCA can help influence policies and regulations within electricity markets by coupling with other models such as optimization, geospatial informatics, net energy analysis, building information, and network theory [44,50,54,58,65,72].

Alternatively, many researchers have proposed sustainability-focused power grid capacity expansion planning with embedded objectives and/or constraints that model environmental impacts. These can be designed to encourage renewable generation technologies or to place limits on non-renewable alternatives (Figure 3). Naturally, one of the easiest ways to expand the power grid in a sustainable fashion is to limit generation options to only renewables and disregard higher-polluting ones. This approach has been adopted by some authors, for instance, in [10,63,73,74]. Alternatively, authors in [75] proposed to incorporate the external costs of energy generation and transmission (e.g., costs due to environmental and societal damages) into the marginal production costs so that it impacts the supply and demand equilibrium. Authors in [76–79] incorporated a cost term in the objective function to reflect emissions. In [80], a carbon tax term was added to the cost objective function.

Authors in [81] introduced cost and revenue functions associated with carbon capture and storage (CSS) for non-renewable technologies. The cost was associated with the installation of the CSS technology, which also uses a nonnegligible portion of the electricity produced by the plant. The revenue was modeled to reflect selling the captured CO_2 as a commodity or tax credits received for capturing carbon.

If financial incentives are allocated to new renewable technologies, their costs need to be included in the model as well. For instance, authors in [82] included a term in their cost function to reflect the incentive payments made by the utility. This term was a linear function of the level of demand reduction (in MW) and energy conservation (in MWh). The former variable was then included in the adequacy constraint, whereas the latter was included in the energy balance constraint. The authors argued that this enables the planning authority to design optimal rates of renewable integration and energy conservation targets.

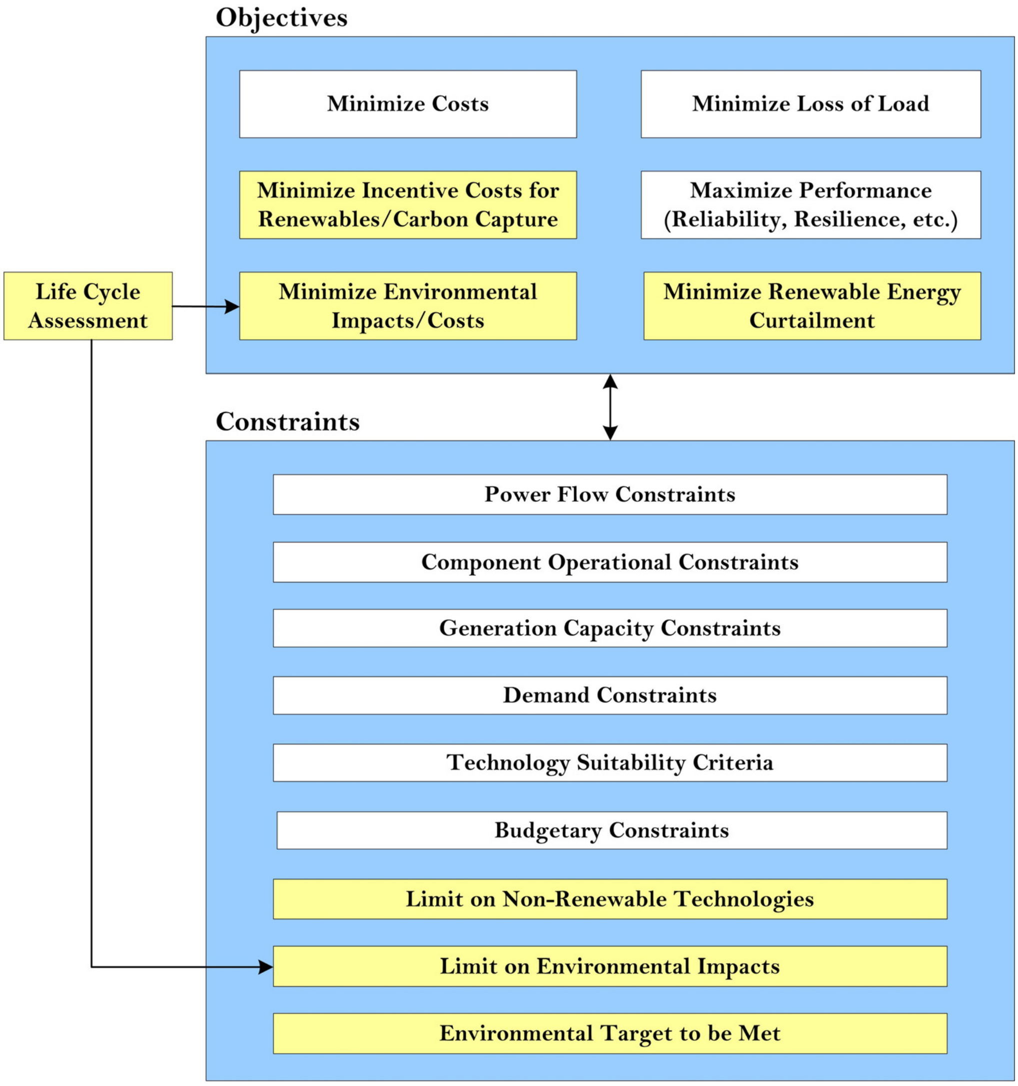

Figure 3. Sustainability-focused grid expansion planning model. Components highlighted in yellow represent objective functions and constraints that target sustainability goals.

Alternatively, installing new renewable plants can be incentivized indirectly by enforcing limits on emissions. Authors in [79,83,84] modeled the problem as minimizing the cost of new technologies to be installed and introduced an additional constraint to limit the emissions from generation. However, as pointed out in the previous section, emissions only account for one aspect of the environmental impacts of new technologies, and an LCA-based approach is the only viable option to model all important undesired impacts. This has been the focus of some researchers in recent years. For instance, authors in [72] developed an optimization framework for a case study in China to allocate energy resources that can supply the load with lower environmental impacts than the business as usual (BAU) model. They considered material input, GWP, and water deprivation as the impact categories. Their objective function was defined as the sum of environmental impacts per unit of each energy resource used to supply the demand, and the model was solved subject to constraints listed as the entire demand being met (overall power balance with no network constraints), limits on the levels of each of the environmental impact categories, and each environmental impact must reduce compared to BAU. The environmental factors for each technology were determined based on a cradle-to-grave LCA analysis. Authors in [71] compared the cost-optimal study of the European power system based on carbon tax incentives with one in which the goal was to minimize environmental impacts, modeled based on a total of 18 indicators. They calculated the annual emissions as a function of the energy mix for 12 representative days in the year and concluded that shifting from an economic to an environment-focused model increased the share of renewables by 2.65% and decreased the overall emissions by 9%. Further, it resulted in upgrading the power grid to accommodate the renewables, leading to a 1.5% increase in the overall cost of the power system. In [85], GHG emissions were incorporated into the grid capacity expansion planning by introducing a new objective function alongside the traditional cost minimization objective. Emission categories were calculated using LCA and combined into investment (for new generation capacity) and operation (for new and existing generation) categories. In their case study, the authors noted an 82% reduction in emissions at the expense of a 63% increase in cost. A similar approach was proposed in [86], where generation expansion planning was combined with LCA into a multi-objective optimization framework. The impacts of the energy supply were divided into a fixed portion, reflecting the costs and impacts associated with the infrastructure construction as well as the upstream processes necessary, and a variable portion, which included costs and impacts associated with the production of electricity. The model was solved subject to constraints associated with power balance, unit capacity limits, and shutdown and start-up of generators, to name a few.

Sometimes the push towards sustainability is guided by a renewable energy target to be met. Authors in [79] introduced constraints that reflected the desired renewable installed capacity and lower/upper bounds for regional expansion of capacity. A similar target for the actual (not nominal) renewable energy capacity was adopted as a constraint in [78]. Authors in [10] introduced a constraint in their model to reflect the wind energy target to be met each year: In each year, the capacity of each wind farm multiplied by its capacity factor, summed over all wind farms, must exceed that year's wind penetration requirement.

Renewable energy resources are intermittent and stochastic in nature, making them different from fossil fuel plants from a reliability perspective. The capacity value of a generation resource, which is defined as the fraction of its rated capacity that is considered firm, should be included in the calculations for determining the amount of reserve margin and/or energy storage capacity needed. To address this, authors in [79] modeled constraints that ensured that secured capacity was higher than peak load of the year. Authors in [87] incorporated the capacity value of variable generation in the form of resource adequacy constraints. Alternatively, the uncertainties of the renewable energy resources can also be modeled in the form of stochastic-based optimization, where first-stage variables indicate installation decisions and second-stage variables concern the operation of the resource under different scenarios. One such example is reported in [15].

Some researchers have also studied the suitability of various generation technologies. For instance, authors in [79] included a suitability objective function modeled as distance to the river for cooling purposes of steam power plants, infrastructure for gas distribution/storage for gas turbines, etc. As another example, authors in [88] developed a fuzzy logic model to rank various green energy alternatives for capacity expansion. They considered social (number of jobs created, balanced development across regions), technical (technology maturity, production capacity), environmental (land requirement, emission reduction), and economic factors (investment cost, affordability of cost of energy).

Other incentives have also been included in the capacity expansion model. As an example, authors in [89] considered the potential of DERs (general resources, not focused on renewables) in reducing the peak load, which could allow for avoiding or delaying the need for capacity expansion (referred to as non-wire alternatives (NWAs)). They considered the timing of grid expansion as a variable, which could be affected by the contribution of those DERs, and investigated whether delaying or avoiding capacity expansion investments would balance the costs of NWAs.

Finally, as the modern distribution grid becomes equipped with a larger number of distributed energy resources, some authors argue that transmission and distribution planning problems need to be combined because, if solved in isolation, the solutions to each one would likely be suboptimal. Such approaches have been proposed, for instance, in [15,90].

Table 3 provides an overview of the various power grid capacity expansion models that have considered sustainability as either a design objective to be optimized or a constraint to be enforced.

Table 3. Overview of approaches to model sustainability in grid capacity expansion formulations.

Ref.	Limit Generation Options to Renewable Technologies	Adjust Marginal Generation Costs Due to Environmental and Societal Damages	COSTS of Emissions as an Objective Function	Carbon Tax as an Objective Function	Cost/Revenue of Carbon Capture as an Objective Function	Incentive Revenue Due to Deploying Renewables as an Objective Function	Hard Constraints on Emissions	Targets for Renewable Generation	LCA Impact Categories as an Objective Function	Constraints for Technology Suitability
[71]									×	
[72]									×	
[63]	×									
[73]	×									
[74]	×									
[10]	×							×		
[75]		×								
[76]			×							
[77]			×							
[78]			×					×		
[79]			×				×	×		×
[80]				×						
[81]					×					
[82]						×				
[83]							×			
[84]							×			
[85]			×						×	
[86]									×	
[88]										×

5. Discussion

5.1. Shortcomings of Existing Grid Expansion Planning Models

With a few exceptions, most of the current power grid capacity expansion models adopt an oversimplified approach to incorporating sustainability into the problem formulation, as discussed in Section 4. Constraints encouraging the deployment of renewable generation technologies often fail to capture the negative environmental impacts over the entire life cycle of the technology. This may be due to the fact that renewable generation technologies such as wind farms and solar parks have generally been proven to be superior to non-renewable alternatives in terms of the environment and society. However, although their environmental and societal impacts are generally dwarfed compared to those of fossil fuels, they can still lead to undesired consequences on the local environment that deserves attention. This needs to be taken into account by a more in-depth analysis of the technology suitability on a case-by-case basis, which may consider the impacts on the local microclimate, ecosystems, and wildlife. Mathematical modeling of technology suitability may not be straightforward due to the lack of data and the generally empirical models. However, it may be incorporated into the problem formulation by ranking and prioritizing potential areas for renewable technology deployment based on offline analysis.

Even when LCA is used for modeling the environmental impacts, the choice of system boundary can have a significant impact. The decision to include upstream and downstream processes may be impacted by the availability and quality of data and can have a significant effect on the outcome of the analysis. These are both critical processes, especially as the penetration level of renewable generation in the power grid increases.

5.2. Shortcomings of LCA

Any LCA must make assumptions because of data imperfections, uncertainties, and/or unavailability. LCA studies evaluating power systems often make assumptions about equipment, transmission systems, electricity mixes, infrastructure lifespan, and transmission losses [42,53,57,61,91]. Assumptions may oversimplify or cause misleading LCA results. The temporal and spatial granularity of data can heavily impact the results of LCA. Improved spatiotemporal methods can benefit a variety of impact categories, such as land-use and particulate matter [92]. Some spatial characteristics that may impact the results of the LCA are the local topography, hydrology, and population density. The development of more regional electricity mixes is an ongoing problem and will resolve as data becomes more accessible. LCA studies of the same technology may result in different outcomes if conducted in different countries due to variations in energy mix and conversion efficiency. Additionally, electricity import and export from/to other grids/markets has created a challenge for LCA analysis as there is no defined methodology to account for the importation and exportation of electric energy [47,49,50]. Temporal characteristics are also critical. For instance, when considering renewable resources that are intermittent, it is important to estimate which kind(s) of fuel sources and emissions they can replace on an hourly or even sub-hourly basis [66]. In general, environmental releases from electricity generation depend on hourly, daily, and weekly demand cycles, seasonal cycles in both environmental conditions and demand, and changes to regional energy systems, including fuel supply, production, and distribution [92]. This may require combining LCA with grid operation dispatch models or even combined fuel-electricity dispatch. Compared to spatial characteristics, temporal aspects are understudied [92]. Further, the results of the LCA will vary depending on the technologies used for the extraction and production of the energy resource and end-of-life recycling of the technology [92]. However, these methods and approaches are highly dynamic and may go through various changes and/or improvements over the timespan of the LCA study.

Scalability is another critical issue with current LCA studies for power systems. The impacts of renewable energy resources such as solar PV or EVs are different at low penetration levels compared to higher deployment rates. At low penetration, the impacts of wind turbines on bird and bat mortality may be negligible. Similarly, the effects of rooftop solar PV in changing the albedo will be insignificant. However, when those resources are deployed at larger numbers and across wider geographical scales, the negative impacts can no longer be ignored.

Some impacts, such as noise pollution, visual pollution, and social justice, are not readily characterized by LCA [66]. Noise, in particular, is difficult to model because environmental mechanisms of sound propagation and attenuation are complex, nonlinear, and highly dependent on local circumstances [66]. In addition, the size of the wind farm, the length and design of the turbines, and the local topography may determine the severity of this type of pollution for a particular region, which may not be generalizable to other wind farms and regions. Similarly, for power transmission lines, changes to the landscape, e.g., when lines cut through forested areas, aesthetic disturbance [75], and electromagnetic noise need to be taken into account. Although, most negative impacts of transmission lines are local in nature.

Considering land use as a standalone impact category, as it is currently done in many LCA studies, may fail to reflect the true effect of generation technologies. This is because renewable generation technologies, although they generally use more land than conventional power plants, do not lead to significant negative impacts. Instead, one should consider impacts such as reversibility of land transformation [66], changes in local microclimate, changes to the grade of the land, and negative impacts on land value.

5.3. Future Research Opportunities

Although LCA-based grid expansion planning considers damage to human health as one of the endpoint impact categories, it does not include all societal aspects of power grid operation, particularly regarding energy justice and equity. Energy justice is typically viewed from the angles of *distributional justice*, which concerns the fair distribution of harms and benefits, *procedural justice*, which is related to fairness in decision-making of electrification projects, and *recognition justice*, which acknowledges and considers the differences in the vulnerabilities and needs of individuals when it comes to access to energy or lack thereof. These aspects of power grid design and operation, especially distributional and recognition justice, need to be considered in future grid planning and can be linked with LCA by defining additional midpoint impact categories. For instance, recognition justice can be modeled based on the number of socially vulnerable populations that are supplied by a particular generation plant. Social vulnerability to lack of access to power can be quantified as a function of certain socioeconomic and demographic factors, for instance, as shown in [93]. Distributional justice can be represented as the geographical distribution of harms and benefits that arise from a particular power plant. While the benefits can be quantified in terms of energy supplied, improved reliability, improved resilience, and/or lowering the cost of electricity, harms may be viewed in terms of the localized environmental impacts, for instance, air quality, particulate matter, and creation of heat islands, or other factors such as noise pollution, aesthetic disturbance, electromagnetic noise, and impacts on land values. Of course, this is a delicate matter to analyze. While generation technologies can lead to negative human impacts, it can also be argued that a general lack of access to electricity in developing countries may also result in health-related consequences [66]. It may therefore be necessary to consider the improvement in health conditions due to electrification to balance the negative effects of generation technologies.

Regional natural disasters or global energy crises caused by economic or geopolitical events may disrupt the availability of some energy resources and put significant strain on the power grid. With modern power systems operating closer than ever to their stability limits, any disruption in energy flows can threaten the reliability and security of the grid. A sustainability-focused view of power grid capacity expansion must, therefore, be balanced against power grid resilience requirements. This is necessary because sustainability and resilience may, at times, seek different objectives. A solution based on sustainability may drive the grid towards utilizing less materials and resources, which in turn may jeopardize its ability to effectively handle HILP events. Power grid infrastructural resilience, on the other hand, promotes grid hardening strategies such as redundant designs and component reinforcements, which may lead to negative impacts on resource availability and material usage. Similarly, operational resilience may require the deployment of redundant energy resources in the form of reserves. To address this issue, it is best to frame the capacity expansion problem as a multi-objective model in which resilience and sustainability are considered within a unified framework. With these objectives being at times contradictory, it is possible to arrive at solutions that are no longer optimal when each of the objectives is considered in isolation.

The findings from LCA studies related to power systems show the importance of energy conservation, energy efficiency, and demand side management strategies in conjunction with the deployment of renewable energy resources. This can be argued from two perspectives. First, it is clear that no perfect generation technology exists, and every energy resource has some level of environmental impact. The forecasted rise in demand until 2050 underlines the need for an aggressive power grid capacity expansion for the next three decades, which is likely to contribute to climate change and material scarcity. Alternatively, energy conservation, energy efficiency, and demand response can be considered viable solutions to offset part of that demand and defer capacity expansion projects as much as possible. In addition, these end-use energy consumption strategies can act as demand flexibility solutions to help alleviate some of the inherent intermittency of wind and solar resources. This could help reduce the need for deploying energy storage systems, especially grid-scale batteries, that are known to have negative impacts on the environment and material usage.

LCA studies are shown to be affected by uncertainty in data. This is especially true in CLCA where the consequences of future scenarios are incorporated into the study and assessed. Because projections on future demand, energy prices, technology maturity, and impacts of various policies are not deterministically known and yet, have significant impacts on the results of the LCA, stochastic models may be developed to properly represent such uncertainties. The latest advances in optimization under uncertainties, for instance, using stochastic programming, robust optimization, and Markov decision processes, can be used to enhance the current LCA models in order to provide a risk-based analysis framework.

6. Conclusions

Power systems' reliance on fossil fuel-based generation technologies is decreasing as nations around the world work to decarbonize their infrastructure to combat climate change. This, in conjunction with a rise in demand due to population growth and system electrification, is causing a need for new generation capacity to be developed, considering alternate energy resources. The negative environmental impacts of fossil fuels are well documented and understood, which is why renewable generation technologies are being prioritized due to their low carbon emissions and significantly lower environmental footprint. However, generation technologies based on renewable energies are not without negative impacts. Although they do not produce nearly as much emission as fossil fuels during their operation, they can still have a considerable environmental footprint associated with material use and processing and end-of-life recycling. Further, the intermittent nature of wind and solar resources may necessitate the deployment of energy storage technologies, which in the case of battery systems, can lead to human toxicity and other environmental effects. Regardless of the technology used, the expansion of power grids to meet the demand does not occur without damaging impacts on human health, ecosystems, and resource availability. It is only through an in-depth analysis of a generation technology over its entire life cycle that it can be evaluated in an objective and unbiased manner. Life cycle assessment is a powerful modeling tool that allows for quantifying the environmental and societal impacts of a generation technology over its entire lifetime. LCA considers not just the global warming potential of different technologies but also the way they interact with the environment in terms of material, energy, and water resources consumed, as well as their impact on air, soil, and water. This makes LCA an invaluable tool to be incorporated into the power grid capacity expansion models. Historically, however, this has not been the case. Power grid capacity expansion projects have mainly only considered costs and energy not served as the main objectives to be minimized. This clearly needs to change. To ensure that power systems do not have detrimental effects on future generations, the sustainability of generation and transmission capacity expansion projects should be considered and incorporated into the problem formulation. This paper provided an overview of LCA as applied to power generation, transmission, and distribution. A review of LCA findings related to the power grid, challenges, and limitations was also presented. This was followed by a discussion of the literature as to how sustainability is currently implemented in grid design and capacity expansion models. The paper concluded with a discussion of shortcomings of sustainability incorporated in grid expansion models, shortcomings of LCA in connection with power systems, and suggested areas for future research.

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