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DISSERTATION

# **GLOBAL ENERGY TRANSITION:** COST DYNAMICS IN THE DIFFUSION OF RENEWABLE ENERGY TECHNOLOGIES

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**Abstract**

This dissertation investigates the cost dynamics shaping the diffusion of renewable energy technologies. Using logistic regression and learning curve models, the study examines the evolution of key energy sources, including solar, wind, nuclear and fossil fuels. The findings indicate that renewable energy technologies, particularly solar and wind, exhibit strong learning effects and an S-curve diffusion pattern, with cost reductions driven by economies of scale, technological advancements and environmental regulations. In contrast, fossil fuels and nuclear power demonstrate cost stagnation or increases, suggesting a diminishing competitive advantage. Projections indicate that renewables will surpass fossil fuels as the primary source of electricity generation by mid-century. However, the rate of transition remains dependent on regulatory frameworks, infrastructure capacity, and geopolitical factors. This research provides a quantitative assessment of energy technology diffusion, contributing to a broader understanding of the economic conditions influencing the renewable energy transition.

Keywords: Global Energy Transition; Renewable Energy Technologies; Solar Photovoltaics; Wind Energy; Fossil Fuels; Nuclear Energy; Technology Diffusion; Learning Curves; Logistic Regression; Levelized Cost of Electricity.

**Resumo**

A presente dissertação analisa a dinâmica de custos subjacente à difusão das tecnologias de energia renovável. Para isso, recorreu-se a modelos de regressão logística e de curvas de aprendizagem para avaliar a evolução de diferentes fontes energéticas, nomeadamente a energia solar, eólica, nuclear e combustíveis fósseis. Os resultados evidenciam que as tecnologias renováveis, em particular a solar e a eólica, apresentam efeitos de aprendizagem significativos e seguem um padrão de difusão de curva em "S", com reduções de custos associadas a economias de escala, progressos tecnológicos e políticas ambientais. Por outro lado, os combustíveis fósseis e a energia nuclear registam estagnação ou acréscimos nos custos, o que sugere uma perda gradual de competitividade. As projeções apontam para que as renováveis ultrapassem os combustíveis fósseis como principal fonte de produção elétrica até 2050. Todavia, há que ter em conta que o ritmo da transição é condicionado pelos quadros regulamentares, pela capacidade das infraestruturas e pelo contexto geopolítico. Este trabalho fornece uma avaliação quantitativa da difusão tecnológica no setor energético, contribuindo para uma compreensão mais ampla das condições económicas que influenciam a transição para as energias renováveis.

Palavras-chave: Transição Energética Global; Tecnologias de Energia Renovável; Energia Solar Fotovoltaica; Energia Eólica; Energia Nuclear; Combustíveis Fósseis; Difusão Tecnológica; Curvas de Aprendizagem; Regressão Logística; Custo Nivelado de Eletricidade.

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## 1. Introduction

The existing global energy system remains misaligned with socio-economic and environmental sustainability objectives (Roser, 2020a). While progress has been made in the adoption of low-carbon technologies (Ritchie, 2021a), reliance on fossil fuels persists. In 2023, fossil fuels accounted for more than 80% of global primary energy consumption, making the energy sector responsible for more than three quarters of global greenhouse gas (GHG) emissions (Ge et al, 2024).

Climate models consistently warn of a narrowing window to mitigate catastrophic climate impacts (IPCC, 2023). The Intergovernmental Panel on Climate Change (IPCC) has emphasized that exceeding the 1.5°C global warming threshold, set by the Paris Agreement, could lead to irreversible damage, including the loss of biodiversity, threats to food security and the displacement of millions due to rising seas and extreme weather events; and argues that to limit warming to 1.5°C, global GHG emissions must reach net-zero by mid-century.

Inspiringly, the past two decades have witnessed a substantial decline in the costs of renewable energy technologies, driven by technological innovation, economies of scale and learning-by-doing (Rubin et al, 2015) which has brought the energy sector closer to achieving net-zero emissions (IRENA, 2024a).

Given these recent developments, understanding the pace and drivers of renewable energy adoption is critical for advancing the transition to a low-carbon energy system. For that reason, this thesis aims to investigate:

1. What are the historical trends in the relative costs of renewable energy technologies compared to non-renewable energy sources and at what rate have these costs declined over time?

2. How have the diffusion rates of renewable energy technologies evolved and what is the projected timeframe for their adoption to surpass fossil fuels as the primary source of electricity generation?

By addressing these research questions, this study assesses how rapidly the costs of renewable energy have declined over time and the extent to which this declining trend has influenced their adoption. Additionally, it identifies the observed patterns in the diffusion of renewables and estimates the timeframe in which they are expected to become the dominant source of electricity generation.

The study begins with a comprehensive literature review in Section 2, which contextualizes the current understanding of cost trends and adoption patterns within the energy sector. Section 3 describes the methodological approaches employed to ensure the study's replicability and transparency. Section 4 presents a detailed analysis of the results, elucidating their significance and interpreting the underlying economic mechanisms. Section 5 discusses the main findings, limitations, and implications in relation to existing knowledge. Finally, Section 6 concludes by summarizing key takeaways from this study and identifying critical areas for future research.

## 2. Literature Review

### 2.1. Theoretical Framework

#### 2.1.1. Evolutionary Economics

In *Capitalism, Socialism and Democracy* (1942), Joseph Schumpeter argues that capitalism is inherently dynamic, characterized by continuous evolution rather than a static state. He asserts that the entry of innovative entrepreneurs serves as a disruptive force that sustains economic growth, even as it dismantles established companies and labourers who once benefited from older technological, organizational, regulatory and economic paradigms (Sidak and Teece, 2009).

Schumpeter saw disruption not as a mere byproduct of economic change, but as a fundamental driving force behind progress and development (Kurz, 2012). A good example of this concept is the transformation of the electric power sector (Mathews, 2017) which represents a fundamental transition in technological, economic and social systems, moving away from fossil fuel dependence.

According to Fagerberg (2025), long-term technological, economic, and social changes result from the dynamic interaction between variation and selection, as variation introduces new ideas and technological advancements, selection determines which innovations are refined, adopted and scaled.

Furthermore, Freeman and Perez (1988) identified a recurring pattern in techno-economic paradigm shifts, wherein each major industrial transformation is driven by a core enabling factor - a resource or technology that is affordable, accessible and applicable. Building on this framework, Mathews (2013, 2014) argues that the ongoing global green transition mirrors historical industrial revolutions, with the declining cost of renewable energy, particularly wind and solar, serving as the primary driver of systemic change (see Section 2.2).

### 2.1.2. Innovation Diffusion Studies

Diffusion studies in the subfield of rural sociology in the Midwestern United States gained momentum, in the late 1920s, as researchers aimed to understand how independent farmers adopted innovations such as hybrid seeds, new equipment and modern techniques.

This ultimately led to a pivotal study conducted, in 1943, by Bryce Ryan and Neal Gross, rural sociologists at Iowa State University, on the adoption of hybrid corn seed, which formalized the diffusion research paradigm (Valente & Rogers, 1995) and became a foundational reference for subsequent work in the field, namely the first empirical study of technology diffusion conducted by an economist – a survey on the adoption of hybrid corn seed, in the Midwestern United States, published in 1957 by Zvi Griliches.

According to Hall (2009), Griliches' work revealed two main insights: the critical role of economic factors such as expected profits and economies of scale in explaining the varying rates of adoption across different states; and, that the variation in initial adoption timelines was influenced by the speed of customization of the seed for specific geographic and meteorological conditions. The latter draws attention to the interactive nature of technological diffusion, i.e. technologies are iteratively adapted to improve their suitability and performance in various contexts.

In 1962, one of the most influential works in this field was published - Everett Rogers' book *Diffusion of Innovations*. As a professor of rural sociology at Ohio State University, Rogers synthesized findings from over 508 studies across multiple disciplines and formulated a comprehensive theory that addressed how innovations spread among individuals and organizations.

According to Rogers (1962), several factors influence the rate of adoption, at the individual level, such as:

- Relative advantage, i.e. the perceived improvement the innovation offers over existing solutions.
- Compatibility with the adopter's existing processes and societal norms.
- Complexity, i.e. the perceived difficulty of understanding and using the innovation.
- Trialability, i.e. the ease with which adopters can experiment with the innovation before adoption.
- Observability of its benefits.

It is important to distinguish between two related but distinct concepts: adoption and diffusion. Adoption refers to the decision-making process by which an individual or organization chooses to implement an innovation, whereas diffusion concerns the cumulative spread of such adoption across a social system over time, typically represented by an S-shaped curve in diffusion theory (see Section 2.1.4).

According to Peres et al (2010), innovation diffusion is “the process of the market penetration of new products and services that is driven by social influences, which include all interdependencies among consumers that affect various market players with or without their explicit knowledge”. Without the process of diffusion, innovation would have minimal social or economic impact. As Josef Schumpeter, pointed out, "As long as they are not carried out into practice, inventions are economically irrelevant" (Schumpeter, 1934, p. 88).

However, diffusion is not merely a pathway for spreading innovations. A crucial aspect, first brought to attention by Griliches (1957) and later emphasized by Rosenberg (1982) is the interaction between diffusion and innovation, more specifically the interactive nature of technological diffusion. As new technologies spread across different environments, producers and users often discover new applications to optimize their production or usage, leading to continuous refinement and adaptation.

Another relevant observation, pointed out by Stoneman and Battisti (2010) is that a country’s usage and/or ownership of technology is not inherently linked to its production – a typical pattern involves a country first importing a technology for local use, then shifting to domestic production to meet internal demand, and eventually expanding production capacity to export the technology, sometimes even back to the original innovator country.

### 2.1.3. Diffusion Modelling

A fundamental distinction in diffusion modelling lies between equilibrium and disequilibrium models (Meade, 2006). Disequilibrium models often suggest that demand growth is self-reinforcing, meaning that adoption accelerates once a critical mass of users is reached. In contrast, equilibrium models take a more static view, assuming that adoption occurs only when expected benefits outweigh costs.

A well-documented pattern in the adoption of new technologies is the S-shaped diffusion curve (Geroski, 2000), when plotted over time, adoption rates typically register this trajectory, characterized by three distinct phases: an initial slow uptake, a period of rapid growth, and eventual market saturation. This pattern is consistently observed across industries and geographical contexts, highlighting the universal nature of technology diffusion.

One prominent explanation for this pattern is the epidemic model, which is widely applied in sociology, marketing (e.g. the Bass Model) and economics. This model draws an analogy between the spread of innovations and infectious diseases. In this framework, adoption occurs as interactions between adopters and non-adopters increase, i.e. the more exposure potential adopters have to existing users, the higher the likelihood of adoption.

This idea was formalized in 1968, by Edwin Mansfield in his *Epidemic Theory of Innovation Diffusion*, which posits that diffusion is primarily driven by asymmetric information distribution. Mansfield's model further emphasizes that much like infectious diseases with varying transmission rates, the speed of innovation diffusion depends on several factors:

- The perceived advantages of the technology, such as cost savings or efficiency gains.
- The structure of social and professional networks, which determines how quickly knowledge spreads.
- The contextual factors influencing adoption decisions, such as industry norms, competitive pressures and institutional constraints.

Another explanation is provided by the probit model (Geroski, 2000), which suggests that consumers perceive varying levels of benefit from new technologies. If the distribution of perceived benefits follows a normal or approximately normal curve, the adoption process will still exhibit an S-shaped pattern, even in cases where technology costs remain unchanged or decline over time.

These models underscore two principal mechanisms of technology adoption (Stoneman, 2010): consumer learning, where adoption spreads via social influence and information exchange; and consumer heterogeneity, wherein individuals derive different levels of benefit from an innovation. Both mechanisms contribute to the characteristic S-curve diffusion trajectory.

According to Meade (2006), there are still two other perspectives that might explain the S-shaped diffusion curve:

- Density dependence models, rooted in population ecology, suggest that two opposing forces - legitimation and competition - govern the diffusion process. In the early stages, as a new technology gains legitimacy, adoption accelerates. However, as competition intensifies, market saturation and competitive pressures slow further adoption.
- Information cascades or models of path dependence suggest that the initial selection of a particular variant of a new technology can influence long-term diffusion. Early adopters' choices create a herd effect, where later adopters follow suit, leading to lock-in effects that can accelerate or constrain overall technology adoption.

### 2.1.4. Energy Technology Diffusion

In the initial stages of their lifecycle, new energy technologies often enter niche markets due to high costs and low efficiency (Grubler et al, 1999). These niche applications serve as testing grounds, where performance rather than cost is the primary driver of adoption.

As energy technologies mature, they move through distinct phases of growth (Wilson, 2012). Beginning with a formative phase characterized by small-scale experimentation and gradual refinement of the technology. This stage is followed by the up-scaling phase, during which larger and more efficient units are developed to capture economies of scale. Over time, as cumulative production and deployment increase, costs decline through mechanisms such as learning-by-doing, economies of scale and process standardization.

As new technologies improve through scaling and learning, they compete with incumbent systems, gradually gaining market share and eventually displacing less efficient or more expensive options (Grubler, 2012).

This dynamic is evident in the case of renewables such as solar photovoltaics (see 2.2.1), which experienced dramatic cost reductions over the past two decades, falling by nearly 90% since the early 2000s; and wind energy (see 2.2.2), which Goldthau & Sovacool (2012) identified as one of the earliest renewable technologies to achieve cost competitiveness with fossil fuels in certain markets, particularly in regions with strong wind resources and supportive policies.

Even though cost competitiveness has been argued as the most consequential driver, it is worth mentioning that there are other factors affecting energy technology adoption. According to Ke et al (2022) those factors are as follows:

- availability (energy-efficient and clean technologies are not evenly accessible across locations and time, creating barriers to widespread adoption).
- knowledge (lack of awareness or ability to understand the benefits of adoption can lead to missed opportunities, even when the technology is economically viable for individuals or companies).
- affordability (high initial costs and limited access to financing hinder adoption, as these technologies often require significant upfront investment).
- gain (the perceived or actual net benefit of adopting the technology is a critical factor influencing decisions by individuals or companies), which is closely related to cost competitiveness.
- willingness to adopt/pay (which is closely tied to the other four factors and reflects the overall readiness of individuals or companies to embrace the technology).

## 2.2. Empirical studies

Rapid innovation is driving this transition by reducing the costs of renewable technologies and enabling technologies like battery storage (Ritchie, 2021b). Ram et al (2018) go as far as suggesting that, by 2030, all G20 countries will achieve full cost competitiveness for renewables. Others, such as Gielen et al (2019) suspect the share of renewable energy in the total primary energy supply could rise from 15% in 2015 to 63% by 2050; and assert that this growth, combined with enhanced energy efficiency, could account for 94% of the emissions reductions required to meet the targets of the Paris Climate Agreement.

This transition to low-carbon energy technologies offers benefits that extend beyond climate protection and energy security. It could drive economic growth through substantial cost savings (Adão et al, 2024) and by fostering job creation (IRENA, 2024d). While the transition demands significant infrastructure investment, particularly in expanding grid capacity, these initial costs are anticipated to be offset by lower long-term energy expenses.

Moreover, such transition involves a structural shift from centralised, fossil fuel-based systems to decentralised, low-carbon energy generation, with electricity becoming the dominant energy sector - it is very likely that the share of electric energy will increase, mainly because a large share of transport will be electrified. A decentralized renewable energy system enhances energy autonomy, strengthens resilience to natural disasters and stimulates local economies (Cerdá et al, 2024).

Despite the significant progress in reducing costs and promoting renewables, several barriers remain that hinder the widespread adoption of renewable energy technologies (Zakeri and Syri, 2015). The relative advantage of renewables has often been obscured by market distortions and infrastructure lock-in favouring fossil fuels due to path dependency (Nemet, 2009). Solar PV and wind power are both dependent on weather conditions, leading to variability in electricity generation, which poses a significant problem as current grid infrastructure in many regions was designed for centralized, fossil fuel-based energy generation, making it ill-suited to accommodate large-scale deployment of renewable energy (Sovacool and Geels, 2016). Furthermore, IEA (2024a) reports that financing remains a major challenge in developing economies, where high costs of capital and political risks discourage investment; and, the global energy market remains concentrated, with China accounting for more than half of global manufacturing capacity, which poses risks to supply chain resilience.

In what follows we will detail relevant aspects of the fast-changing economics of each of the main energy technologies with greater potential to drive the current energy transition. Although hydrogen is not included in the scope of the analysis, it deserves an honourable mention due to its significant potential as a future energy carrier.

### 2.2.1. Solar power

The modern silicon-based solar cell was invented by Bell Labs in the U.S. in 1954. Initially, it was used in the satellite industry and remained extremely expensive. However, the 1970s brought significant changes to solar technology and its industry, especially after the 1973 Arab Oil Embargo, which caused oil prices to quadruple in three months, making energy security a key issue in countries like the U.S. and Japan.

In response, President Nixon launched "Project Independence" and the U.S. government invested 1.7 billion dollars in solar energy research and development (R&D) between 1974 and 1981. During this time, institutions like the Department of Energy (DOE) and the Solar Energy Research Institute (SERI), later renamed the National Renewable Energy Laboratory (NREL), were established.

New policies also emerged, including California's Interim Standard Offer Contract #4, an early feed-in tariff later refined by Germany's Renewable Energy Sources Act (EEG). However, after President Reagan took office in the 1980s and fossil fuels became cheaper and more abundant, solar energy lost priority and the U.S. solar program was dismantled.

Japanese companies entered the solar photovoltaics (PV) industry around the same time as U.S. companies but followed a different path to success. Backed by strong and consistent R&D support from the 1974 Sunshine Project, they found profitable niche markets in consumer electronics, such as calculators and toys, to sell their PV products.

As these niche markets became saturated, Japan's Ministry of International Trade and Industry (MITI) introduced a rooftop subsidy program in the 1990s, combined with net metering regulations, to create demand for solar installations. These initiatives helped Japanese solar firms dominate the global market, becoming the largest in the world until they lost their lead after 2005.

Although Japan eventually lost its leadership, its contributions significantly advanced solar technology. Japan pioneered large-scale manufacturing processes and showcased the cost-reduction benefits of scaling up through initiatives like the Rooftop Project. These efforts set the stage for countries like Germany and China to adopt and further refine these technologies, enabling mass production and driving solar industry growth.

In 1998, after two decades of building an advocacy coalition, a policy window opened when the Green Party became a ruling partner, leading the German Parliament to pass the

Renewable Energy Law (EEG) in 2000. From 2004 to 2012, the EEG supported the adoption of over thirty gigawatts of PV in Germany with a subsidy program that totalled over two hundred billion euros. The program transformed the global solar market, which grew by a factor of thirty, with Germany accounting for half of global PV installations.

By 2012, the price of PV modules had dropped by 16% compared to pre-EEG levels. This reduction in costs was crucial because it stimulated both demand for solar PV and the ability for solar energy to be integrated into electric grids on a larger scale.

The EEG has been referred to as Germany's "Gift to the World" as it proved that transitioning to renewable energy was more feasible and affordable than previously thought, influencing Germany's *Energiewende* policy in 2010 and the Paris Agreement in 2015.

Activities in China, between 2000 and 2016, also contributed to cheaper PV technology. During this period, Chinese solar companies scaled up production by a factor of five hundred, establishing China as the global leader in solar manufacturing – a position it has maintained to this day, e.g. in 2023, China was responsible for 93% of the global polysilicon supply for solar cells.

According to Nemet (2019), the main driver of China's transition from a nascent PV sector to a global leader was high-risk entrepreneurial activity, exemplified by Suntech. This pioneering company established a model that other firms followed, successfully engaging municipal governments, building a domestic supply chain, training a skilled labour force, and partnering with foreign firms to access international markets.

A pivotal moment in China's path to success was Suntech's Initial Public Offering (IPO), in New York, in 2005. This event not only legitimized the Chinese PV industry on a global stage but also unlocked seven billion dollars in capital from U.S. markets for Chinese PV firms by 2007.

Domestically, the 2005 Renewable Energy Law, though primarily targeting wind energy, signalled a commitment to long-term PV market growth and the introduction of a Chinese Feed-in Tariff, in 2011, helped sustain the industry after the global financial crisis and the slowdown of German subsidies.

Some argue that China's leadership in the PV industry was primarily driven by aggressive investments, substantial government subsidies, and strategic advantages such as access to a large domestic market, low-cost coal-fired energy, and factory locations near coal mines to minimize logistics costs (The Economist, 2024).

However, equally important was China's strong foundation in semiconductor R&D, early PV production and expertise in high-volume manufacturing sectors like textiles. Such foundation alongside international collaborations and the return of Chinese scientists trained abroad allowed Chinese firms to strengthen their global position by meeting international technology standards and certifications, which helped alleviate scepticism among early adopters, especially in Germany.

### 2.2.2. Wind power

Wind energy has been utilized for thousands of years, with early evidence of its use dating back to 5,000 BC, when it was harnessed to propel boats along the Nile River. By 200 BC, wind-powered water pumps were being used in China, and windmills were grinding grain in the Middle East. By the 11th century, wind-powered pumps and mills were utilized for food production. However, it was only in the late 1800s that small wind turbines were widely used for electricity generation (U.S. Energy Information Administration, 2023).

Around 1900, Danish inventor La Cour, with support from the Danish government, initiated one of the first R&D programs focused on electricity-generating windmills. Denmark, like many other nations, shifted toward centralized energy systems powered by fossil fuels, but the vulnerabilities of these systems during World War II, particularly the reliance on imported fuels, prompted La Cour's student Johannes Juel to propose a windmill capable of delivering electricity to the national grid. Juel's windmill was completed in 1957 and operated successfully for over a decade, but Denmark continued to prioritize fossil fuels due to their perceived abundance and low cost (Fagerberg, 2025).

The energy crises of the 1970s spurred governments and researchers to invest in renewable energy, leading to advancements in wind turbine technology, e.g. federal support for large-scale wind turbine R&D gave rise to the installation of thousands of turbines in California by the 1980s. In the following decades, tax incentives and funding for renewable energy contributed to significant growth in wind power, with its share of electricity generation in the U.S. rising from under 1% in 1990 to 10.2% in 2022.

Wind energy also grew rapidly at a global level, with Europe expanding wind power through financial incentives and China emerging as the largest producer. By 2021, at least 128 countries generated approximately 1,808 billion kWh of wind electricity (U.S. Energy Information Administration, 2023).

Denmark played a pivotal role in this expansion, overcoming early challenges like high costs and inconsistent turbine quality. Early efforts were supported by knowledge-sharing associations and grassroots initiatives, leading to the establishment of wind-turbine cooperatives known as "*vindmøllelav*". Danish policymakers introduced subsidies and regulatory innovations (IRENA, 2013), such as the 1984 feed-in tariff, which allowed turbine owners to sell excess electricity to the grid at fair prices. These measures helped foster a growing industry, with companies like Vestas emerging as global leaders. Denmark's success influenced countries like Germany, which adopted similar policies in 1990, contributing to the global wind energy boom.

### 2.2.3. Nuclear power

Nuclear energy, currently responsible for about 10% of global electricity production (Ritchie and Rosado, 2020), has been a key part of the global energy mix since the early 1950s. In the 1970s and 1980s, nuclear power expanded rapidly as governments embraced it as a clean and reliable source of electricity. This growth was driven by technological advancements, rising energy demands, and a desire to reduce reliance on fossil fuels (National Grid, 2024). However, by the 1990s, safety concerns, exacerbated by high-profile accidents, led to stricter regulations and a decline in public support for nuclear energy (Ritchie, 2021a).

Today, much of the nuclear infrastructure is aging, with many plants approaching the end of their operational lives and addressing safety and waste management has significantly increased the cost of new nuclear plants. Small Modular Reactors (SMRs) have been proposed as more flexible and cost-effective solutions, but they face similar challenges as traditional reactors, including safety and waste disposal concerns. Moreover, few SMRs are operational and their ability to meaningfully contribute to the energy transition remains uncertain (Fagerberg, 2025). However, many perceive SMRs to have a future role as complementary to both solar and wind energy, given the intermittency of these renewable energy technologies (Zarębski and Katarzyński, 2023).

Nuclear fission remains the dominant method for generating nuclear power, though fusion has long been considered a promising alternative (Moynihan and Bortz, 2023). Fusion remains far from commercial viability, nevertheless it offers numerous benefits, such as abundant fuel sources from seawater and lithium and inherent safety due to its lack of chain reactions and reduced radioactive waste.

A significant milestone came, in 2022, when the UK government announced plans for the world's first fusion power plant, slated to begin operations by the 2040s (National Grid, 2024). But given the lengthy development timeline, fusion is unlikely to play a significant role in the near-term global energy transition.

#### 2.2.4. Hydrogen power

In 2022, hydrogen accounted for less than 2% of Europe's total energy consumption, with its primary application being the production of chemical products such as plastics and fertilizers (European Commision, n.d).

Hydrogen is a highly flammable gas with significant potential to replace fossil fuels in various applications (Mathews, 2022). However, the current landscape of hydrogen production is reliant on fossil fuels. Approximately 96% of hydrogen is produced via the extraction of hydrogen from natural gas, a method known as "grey hydrogen," which generates considerable $CO_2$ emissions.

To mitigate these emissions, a method called "blue hydrogen" has been proposed, where the carbon dioxide produced during hydrogen extraction is captured and stored. While this approach reduces emissions, carbon capture and storage (CCS) technologies are both technically complex and financially demanding (National Grid, 2023).

An alternative to grey and blue hydrogen is "green hydrogen," produced through the electrolysis of water, using renewable electricity to separate hydrogen from oxygen, making it a cleaner and more environmentally sustainable option (IEA, 2024b).

According to Fagerberg (2025), the role of hydrogen remains uncertain but promising: it could be particularly valuable in long-distance energy transport where electricity cables are impractical, offering a potential solution for energy storage and transfer across vast distances and it could also replace fossil fuels in hard-to-decarbonize sectors like long-haul shipping and aviation, which account for about 6 to 7% of global carbon emissions.

### 2.3. Analytical Framework

This section examines two foundational concepts - learning curves and energy-GDP elasticity - that will support the analysis of both cost trends and diffusion trajectories of renewable energy technologies.

#### 2.3.1. Learning Curves

According to Way et al (2022), fossil fuel prices have remained stable for over a century due to a “running-to-stand-still” dynamic, where advancements in extraction are offset by the need to exploit less accessible resources. Similarly, CCS has shown no cost reductions despite decades of commercial use, and nuclear power has even seen cost increases.

Conversely, other studies have identified certain renewable energy sources, particularly solar photovoltaics, and onshore wind, as the most cost-effective sources of electricity based on their levelized cost of electricity (Timilsina, 2021).

Fossil fuels continue to be cost-competitive primarily due to their lower upfront costs. However, renewable energy technologies are steadily gaining market share, driven by declining costs (Reddy, 2018). This cost reduction is attributed to learning curves, a phenomenon where the cost of renewable energy technologies decreases with each increase of cumulative installed capacity

According to IRENA (2024b), among all renewable energy technologies, solar PV has seen the most significant cost reductions. From 2010 to 2023, the global weighted-average cost of electricity from solar decreased by 90%, driven by advancements in PV cell efficiency, reduced silicon and other material costs, and optimized manufacturing processes. Wind energy has also achieved significant cost declines, though at a slower pace, with onshore wind costs decreasing by 70% and offshore wind by 63%, from 2010 to 2023, due to improvements in turbine design, installation logistics and grid integration.

In contrast, fossil fuels and nuclear seem not to be experiencing learning curves anymore (Kåberger, 2018) which explains why non-renewable energy technologies have shown cost trajectories that increasingly disadvantage them in the evolving energy market, e.g. coal, historically one of the cheapest sources of electricity, is becoming less competitive due to stricter environmental regulations, carbon pricing mechanisms and higher maintenance costs for aging infrastructure (IEA, 2019).

McNerney et al (2011) argues that, unlike renewable energy technologies, there is little room for improving the efficiency of coal power plants, mainly because the price of electricity from fossil fuels is not only determined by the technology itself, it relies significantly on fuel costs, which make up about 40% of total expenses i.e. even if the price for constructing the power plant would decline, the price of the fuel means that there is a floor below which the price of electricity cannot pass.

Over the past decade, electricity generated from natural gas has become cheaper, which may initially seem paradoxical. However, this decline is not part of a consistent long-term trend, as current gas prices remain higher than they were two or three decades ago (Rubin et al, 2015). Like coal, gas power generation is heavily influenced by market conditions and fuel costs, and its potential for technological efficiency gains is limited.

Nuclear energy represents a complex case in the context of the transition to low-carbon energy sources (Adler et al, 2020). While it provides a stable, low-carbon electricity supply, its adoption is significantly hindered by several factors, including high upfront capital costs, long construction timelines and rigorous safety standards. The legacy of high-profile incidents such as Fukushima has also led to increased regulatory costs, further diminishing the economic competitiveness of nuclear energy.

Despite these challenges, nuclear energy could still play a critical role in a future low-carbon energy mix (Berthélemy and Rangel, 2015), particularly by addressing the intermittency of renewable sources and offering significant land-use advantages. Nuclear power requires substantially less land compared to large-scale solar and wind installations, making it a potentially more efficient option in terms of spatial requirements (Ritchie, 2022).

### 2.3.2. Energy-GDP elasticity

In recent decades, global Gross Domestic Product (GDP) has grown at a faster rate than energy consumption, primarily due to advancements in energy efficiency, driven by the expansion of renewable energy and electrification; and, structural shifts toward less energy-intensive activities, such as the transition from manufacturing to service-based industries (Ritchie, 2021c). This trend reflects the phenomenon of decoupling, wherein many countries are reducing their dependence on energy consumption to sustain economic growth. Consequently, the elasticity of energy consumption with respect to GDP has been declining.

Energy-GDP elasticity is defined as the percentage change in energy consumption associated with a one-percent change in national GDP, i.e. $Elasticity = \%\Delta Energy\ Consumption/\%\Delta GDP$. This measure serves as an indicator of the energy intensity of economic activity, reflecting how changes in GDP influence energy demand.

Economic development generally follows a structural transformation process, whereby economies transition from an agriculture-based system to industrialization and, ultimately, to a service-oriented structure. This transition is reflected in energy consumption patterns, as changes in the energy mix accompany economic growth.

Empirical studies indicate that energy-GDP elasticity tends to be higher in high-income countries, largely due to their greater reliance on commercial energy sources rather than traditional biofuels (Burke and Csereklyei, 2016). However, in the long run, energy-GDP elasticity remains below unity, suggesting that economic growth is generally accompanied by reductions in energy intensity and improvements in the overall economic productivity of energy use.

Beyond aggregate energy-GDP elasticities, electricity-GDP elasticities provide additional insights into the relationship between economic activity and energy demand (Liddle et al, 2023). If economic growth drives a shift toward increased electrification, electricity-GDP elasticities should exceed overall energy-GDP elasticities, reflecting the growing role of electricity in economic expansion.

## 3. Methodology

This chapter outlines the methodology used to analyse the historical evolution of renewable and non-renewable energy technologies and, in a subsequent moment, to forecast their deployment. It details the selection and compilation of cost and diffusion indicators (Section 3.1) and the adopted analytical strategy (Section 3.2), highlighting data sources and limitations.

### 3.1. Data Collection

This research primarily examines historical cost data for renewable energy technologies (e.g., solar and wind) and non-renewable energy technologies (e.g., coal, oil, natural gas, and nuclear). The cost analysis focuses on the Levelized Cost of Electricity (LCOE) data sourced from the annual IRENA Report on Renewable Power Generation Costs for the period 2010–2023. It is important to note that, due to some data constraints the LCOE values for combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT) and coal were obtained from the arithmetic mean of 20 countries, with standard deviations of 0.035656511, 0.06448061 and 0.037372974, respectively.

To complement the assessment of cost influence on the adoption of renewable energy, data on the evolution of relevant diffusion indicators – cumulative installed capacity, energy consumption and electricity generation - have been compiled from the following sources: the annual IRENA (2024c), Our World in Data (2023) and IEA (2024c) for the period 2000–2023. As noted, the diffusion indicators selected in this study are supported by a more extensive dataset, spanning a longer period.

This study examines global trends while providing a regional analysis based on income classifications, including high-income, upper-middle-income, lower-middle-income and low-income countries. This analysis includes energy-GDP and electricity-GDP elasticity, utilizing GDP data at constant 2015 prices, sourced from the World Bank.

The second part of this study consists of forecasting the deployment of renewable and non-renewable energy technologies, which requires defining an upper limit and specific year that represents market saturation. For that purpose, data were collected from sources such as BP (2024), Statista (n.d) and IEA (2024c).

The year 2050 was selected as it represents the longest available projection horizon and the same forecasting exercise was applied for total electricity generation by source. However, data constrains for both solar and wind did not allow the prediction of energy consumption by source. Solely total global energy consumption could be analysed, which was particularly useful to assess the expected contribution of the electricity sector. In an effort to standardize reporting, the diffusion caps for 2050 were derived from the "current policy scenario". Though, alternative caps, such as those under the net zero scenario, could have been adopted, potentially leading to significantly different projections.

### 3.2. Data Analysis

Taking into consideration the research questions, this study employs a descriptive model that facilitates the evaluation of both historical and projected trends and ensures that the findings contribute to nuanced understanding of long-term energy trends.

### 3.2.1. Logistic Regression

Building upon Griliches (1957), this study employs a logistic growth curve to model the evolution of cumulative installed capacity in energy technologies. The logistic function provides an effective approximation of cumulative adoptions ($N^t$) within a population of potential adopters ($N^*$), capturing the dynamics of technological diffusion:

$$N^t = N^*/1 + exp(-a - bt) \quad (1)$$

where a and b are parameters governing the adoption process over time. By applying a linear transformation to the logistic equation, we obtain:

$$ln(N_t/N^* - N_t) = a + bt \quad (2)$$

This transformation facilitates estimation of the parameters a and b using time-series data on cumulative installed capacity, given an assumed upper limit $N^*$representing the market saturation level.

To better capture the adoption dynamics, Mansfield (1961) expressed the proportion of non-adopters who transition to adopters between periods t and t+1 as:

$$w_t = (N_{t+1} - N_t)/(N^* - N_t) \quad (3)$$

Which can be rewritten as a differential equation:

$$dN_t/dt = b(N_t/N^*)(N^* - N^t) \quad (4)$$

This standard logistic function describes a diffusion process where the adoption rate ($dN_t/dt$) depends on the interaction between adopters ($N_t$) and non-adopters ($N^* - N^t$), with b representing the "infectiousness" of adoption, akin to epidemiological models. The initial stage (t = 0) assumes limited awareness of the technology, but as leading firms adopt, positive externalities reduce uncertainty, accelerating diffusion.

When this framework is applied to energy technologies, the sigmoid diffusion pattern emerges due to asymmetric information distribution across market participants. The estimated parameter b is called “diffusion coefficient” and will provide insights into the speed of technology adoption.

### 3.2.2. Learning Curves

The study of historical cost trends in wind and solar energy and the forecasting of future developments has employed various analytical approaches (Bolinger et al, 2020). Among these, learning (or experience) curves remain the most widely adopted framework.

Although some studies (e.g., IRENA, 2024b) have explored LCOE-based learning rates for wind and solar energy, the existing literature predominantly relies on one-factor learning curve models that correlate cumulative installed capacity with capital costs.

This study will employ the levelized cost of electricity as the cost metric. LCOE accounts for capital costs, operational expenses, plant performance, financing costs and taxes (as shown in Equation 5) thus offering a more comprehensive and accurate measure of the cost per unit of energy produced.

$$\text{LCOE} = \frac{(\text{CapEx} * \text{Capital Recovery Factor} * \text{Tax Factor}) + \text{OpEx}}{\text{Annual Energy Production (AEP)}} \tag{5}$$

However, this metric does not come without its limitations, namely its restriction to the 2010 – 2023 period and the omission of exogenous factors influencing LCOE, as pointed out in the IRENA reports.

Several studies argue that one-factor models often demonstrate superior descriptive analysis compared to two-factor models (Dai et al, 2024). Consequently, this study adopts a one-factor learning curve model based on LCOE (2023 USD/kWh) and cumulative installed capacity (MW).

The basic formulation of the learning curve, referred to as the one-factor learning curve (FLC), models unit costs ($C$) as a function of cumulative installed capacity ($Q$). $C_0$ and $Q_0$ represent unit cost and cumulative installed capacity at the initial time and $b$ the learning coefficient.

$$C_t = C_0 \left(\frac{Q_t}{Q_0}\right)^{-b} \tag{6}$$

For analysis convenience, this relationship will be plotted as an exponential function on a log-log scale (Upstill and Hall, 2018).

The associated *learning rate* (LR), i.e., $1 - 2^{-b}$ indicates the percentage of cost decrease for each doubling of cumulative installed capacity.

## 4. Analysis

### 4.1. Energy- GDP and Electricity-GDP Elasticities

The global energy-GDP elasticity is 0.674, as observed in Table 1, which is in accordance with previous studies that have estimated the long-run elasticity to be approximately 0.7. This consistency suggests that, on average, energy consumption is increasing at a slower rate than GDP, corroborating the notion of decoupling. The electricity-GDP elasticity, however, is notably higher at 1.002, indicating that electricity consumption is growing at least proportionally with GDP.

| *Income Group* | *Energy-GDP Elasticity (%)* | *Electricity-GDP Elasticity (%)* |
|---|---|---|
| *World* | 0.674 | 1.002 |
| *High Income* | -0.050 | 0.398 |
| *Upper Middle* | 0.727 | 1.016 |
| *Lower Middle* | 0.669 | 0.915 |
| *Low Income* | 0.142 | 0.680 |

Table 1: Mean Long-Run Energy-GDP and Electricity-GDP Elasticities

Source: Own elaboration.

A distinctive observation is the negative energy-GDP elasticity (-0.050) in high-income countries, indicating a slight decline in total energy consumption for every unit of economic growth.

In contrast, upper-middle and lower-middle-income countries exhibit positive and higher energy-GDP elasticities (0.727 and 0.669, respectively), indicating a stronger correlation between energy consumption and economic growth. Nonetheless, both values remain below unity, suggesting that these economies are beginning to experience efficiency gains and structural transformations toward less energy-intensive industries.

Low-income countries display a positive but lower energy-GDP elasticity (0.142), suggesting a weak correlation between economic growth and energy consumption. This could be attributed to a continued reliance on traditional biofuels and non-commercial energy sources, which are less directly linked to formal economic output.

Another significant observation is the fact that, for all income groups, the electricity-GDP elasticities exceed their respective energy-GDP elasticities. The electricity-GDP elasticity in high-income countries is the lowest but it remains positive (0.398), suggesting that while total energy demand is decreasing, electricity consumption continues to rise, albeit at a slower pace relative to GDP.

### 4.2. LCOE learning curves and learning rates

As seen in the methods' section, the learning curve approach demonstrates the relationship between cost reductions and technological performance improvements, emphasizing how advancements in technology and accumulated experience contribute to decreasing costs. The learning coefficient (b) quantifies the rate at which costs decline with cumulative installed capacity, while the learning rate $(1 - 2^{-b})$ represents the percentage decrease in costs each time capacity doubles. These values indicate the scalability and economic viability of each technology in the transition to sustainable energy systems.

Figure 1 illustrates the learning curves for different renewable energy technologies, among them, onshore wind exhibits the highest learning rate at 43.7%, indicating that its costs decline most rapidly as deployment increases. Solar PV and concentrated solar power (CSP) follow closely, with learning rates of respectively 38.5% and 37.2%, demonstrating strong learning effects. In contrast, offshore wind has the lowest learning rate at 21.6%, suggesting that cost reductions occur at a slower pace despite increasing installed capacity.

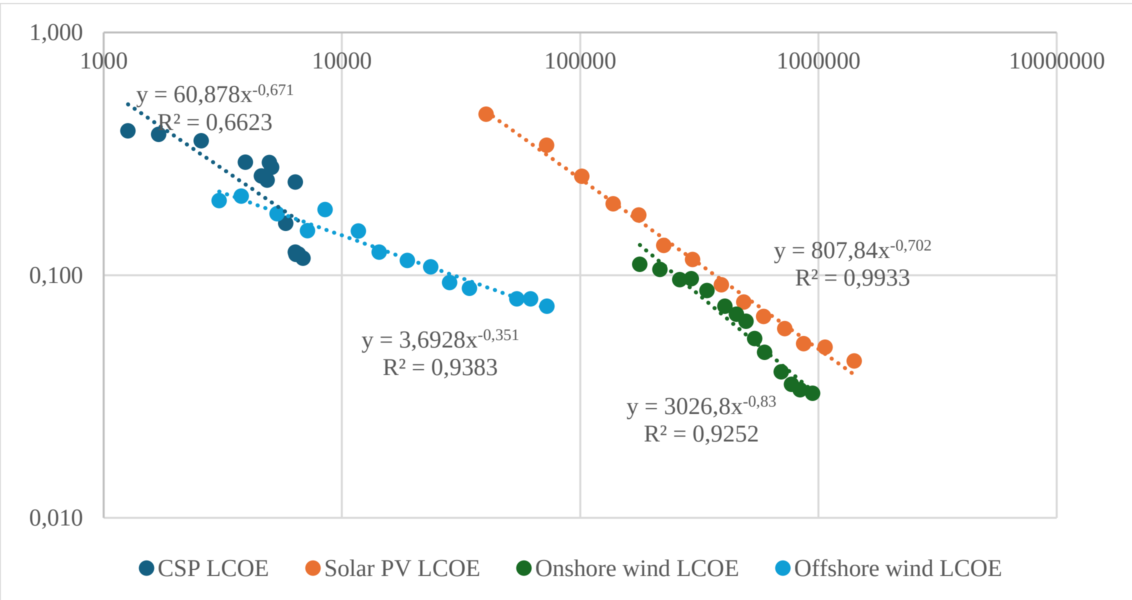

Figure 1: Levelized cost of electricity learning curves, 2000-2023

Source: Own elaboration

Solar PV has the highest $R^2$ value (0.9933), signifying an outstandingly strong correlation between installed capacity expansion and cost reduction. This suggests that solar PV follows a well-defined and predictable learning curve, making it one of the most reliable technologies in terms of cost declines. Onshore wind ($R^2 = 0.9252$) and offshore wind ($R^2 = 0.9383$) also exhibit strong correlations, indicating that cost reductions for these technologies are highly dependent on cumulative deployment, though with slightly more variability than solar PV. Conversely, CSP has the lowest $R^2$ value (0.6623), suggesting a relatively lower predictability of CSP's learning curve and, consequently a high level of uncertainty in achieving cost reductions through scaling alone.

Nonetheless, the high $R^2$ values for most technologies suggest that cumulative deployment is a reliable predictor of cost declines, reinforcing the importance of scaling up renewable energy investments.

Unlike renewables, non-renewables do not register learning curves, which can be easily visualized (see Table IV, in Appendix). Fossil fuels exhibit more stable costs. From 2000 to 2023, coal and combined cycle gas turbine (CCGT) have even exhibited an upward trend in costs, showcasing an estimated Compound Annual Growth Rate (CAGR), of 1.86% and 0.85% respectively. Oil and open cycle gas turbine (OCGT) have remained nearly constant, with marginal reductions of 0.07% and 0.01%, which contrasts sharply with the cost reductions of solar and wind technologies.

Unsurprisingly, as of 2023, renewable energy sources such as solar and wind are widely recognized as more cost-effective than fossil fuels (see Table IV, in Appendix). The estimated Levelized Cost of Electricity (LCOE) per kilowatt-hour (kWh) for CSP, solar PV, onshore wind and offshore wind is approximately 0.117, 0.044, 0.033 and 0.075, respectively. In contrast, the LCOE for fossil fuel-based energy sources, including oil, CCGT, coal and OCGT is estimated at 0.357, 0.121, 0.134 and 0.121, respectively.

## 4.3. Diffusion Indicators

### 4.3.1. Energy Consumption and Electricity Generation

Total energy consumption has increased steadily, with a CAGR of 1.87% (see Table V, in Appendix). However, growth rates vary significantly across energy sources. Fossil fuels still dominate global energy consumption, but their growth is relatively slow compared to renewable sources.

Coal, gas and oil registered a CAGR, from 2000 to 2023, of 2.14%, 2.16% and 1.00% respectively, making gas the fastest-growing fossil fuel. Whereas solar has an exponential growth, with a CAGR of 35.08%, far outpacing the other sources. Wind power has also expanded rapidly, with a CAGR of 19.00%. Conversely, nuclear energy supply has declined slightly, with a CAGR of -0.29%, suggesting policy and economic challenges in expanding nuclear capacity.

Total electricity generation has also increased steadily, with a CAGR 2.78% (see Table VI, in Appendix), higher that total energy consumption, further corroborating the increased electrification of the energy sector – in 2023, electricity generation represented 19.25% of total primary energy consumption.

A noteworthy observation is the significant structural changes in electricity generation, particularly the rapid expansion of renewable energy sources. Solar and wind power exhibited the highest growth rates, with CAGRs of 35.93% and 19.64%, respectively, with their combined market share (of total electricity generation) increasing substantially from 0.211% in 2000 to 13.346% in 2023, underscoring the accelerating transition toward low-carbon energy sources. In contrast, nuclear power has seen limited growth, with a CAGR of 0.23%.

Over the past two decades, nuclear's share of total electricity generation has declined approximately 2.48%, as shown in Table 2, a decrease only surpassed by the oil sector, which experienced a significant market share decline of 4.78%. Both energy sources lost market share in total energy consumption as well.

| | ***Share of total energy consumption in 2023 (%)*** | ***Energy Market share growth between 2000-2023*** | ***Share of total electricity generation in 2023 (%)*** | ***Electricity market share growth between 2000-2023*** |
|---|---|---|---|---|
| ***Coal*** | 26.47 | 0.26 | 35.51 | -0.28 |
| ***Gas*** | 23.30 | 0.29 | 22.47 | 0.94 |
| ***Oil*** | 31.70 | -0.85 | 2.67 | -4.78 |
| ***Nuclear*** | 3.96 | -2.12 | 9.11 | -2.48 |
| ***Solar*** | 2.48 | 32.61 | 5.53 | 32.25 |
| ***Wind*** | 3.51 | 16.82 | 7.82 | 16.41 |

Table 2: Share of total energy consumption and total electricity generation in 2023 and respective Compound Annual Growth Rates from 2000 to 2023

Source: Own elaboration

Coal, still the dominant source of electricity, accounted for 35.51% of global electricity generation in 2023. However, its market share has slightly decreased, approximately 0.82% and despite its continued prominence, coal's CAGR of 2.48% (see Table VI, in Appendix) suggests a slowing growth rate. Natural gas, by contrast, has outpaced coal with a CAGR of 3.74%.

Predictably, both solar and wind have seen a steep increase in their share of total energy consumption and total energy generation, which aligns with their estimated CAGRs.

### 4.3.2. Cumulative Installed Capacity

The installed capacity of solar and wind power has experienced the most significant expansion, with a CAGR, from 2000 to 2023, of 34.21% and 18.59% respectively. In contrast, nuclear energy has exhibited relatively slow growth, with a CAGR of 0.49%, indicating stagnation in new capacity additions. Fossil fuel-based electricity generation, while still dominant within the global energy mix, has grown at a comparatively modest CAGR of 2.88%.

While the growth rates of nuclear and fossil fuel-based energy remain relatively stagnant, solar and wind power installations have demonstrated significant volatility, particularly in the early years of adoption. However, since 2015, these fluctuations have given way to more stable and sustained expansion, suggesting that the renewable energy sector has reached a phase of maturity and predictability in deployment.

Furthermore, the high correlation coefficient (0.979) between installed capacity and energy consumption suggests that as new energy capacity is added, electricity demand is being met more efficiently. Similarly, the correlation between installed capacity and electricity generation (0.985) indicates that investments, particularly in renewable energy technologies, are directly translating into increased electricity output.

### 4.4. Logistic regression

The regression analysis of solar, wind, nuclear and fossil fuel installed capacity over time provides critical insights into the intrinsic growth rate of each energy source. The application of a logistic regression model (as shown in Figure 2) suggests that renewable energy sources, particularly solar and wind, exhibit rapid growth, while nuclear and fossil fuels follow more moderate trends.

Solar energy demonstrates the most significant expansion, as indicated by the equation y = 0.3432x - 694.76. The relatively high coefficient of 0.3432 reflects the accelerated deployment of solar capacity. Similarly, wind energy follows a logistic trajectory with y = 0.1964x - 397.47, indicating steady but slightly slower adoption speed compared to solar.

Conversely, nuclear energy exhibits a much flatter trend, as reflected in the equation y = 0.0488x - 96.014y, suggesting limited expansion in installed capacity. Fossil fuels, despite experiencing faster growth than nuclear, still show a modest increase with y = 0.1314x - 263.04. The estimated diffusion coefficient of 0.1314 indicates that while fossil fuel infrastructure is still expanding, its relative increase is significantly lower than that of renewables.

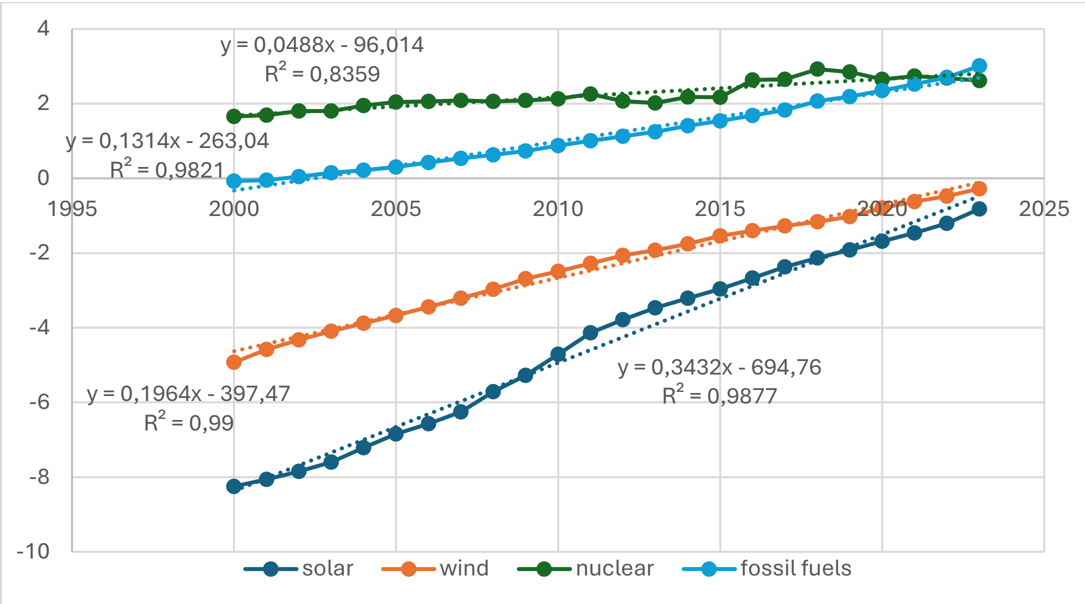


Figure 2: Logistic regression of the installed capacity (MW) of solar, wind, nuclear and fossil fuels from 2000 to 2023

Source: Own elaboration

The high $R^2$ values across all energy sources indicate strong model fits, confirming the validity of the logistic growth assumption for installed capacity projections.

Projections based on the logistic regression trends indicate that solar and wind energy follow distinct S-curve trajectories (see Figure 3), with solar reaching its saturation point around 2035 and wind experiencing a more gradual ascent, stabilizing closer to mid-century. The steep initial growth of these technologies reflects the exponential phase of their respective S-curves, driven by cost reductions, policy incentives and technological advancements. However, as they approach market saturation, growth slows due to infrastructure limitations, grid constraints, and diminishing marginal efficiency gains.

Fossil fuels, in contrast, appear to have already entered the plateau phase of their S-curve, signalling stagnation or potential decline as renewable adoption accelerates. Meanwhile, nuclear energy remains relatively stable with minimal deviation from a linear trend, suggesting that it does not follow the same logistic growth dynamics as renewables.

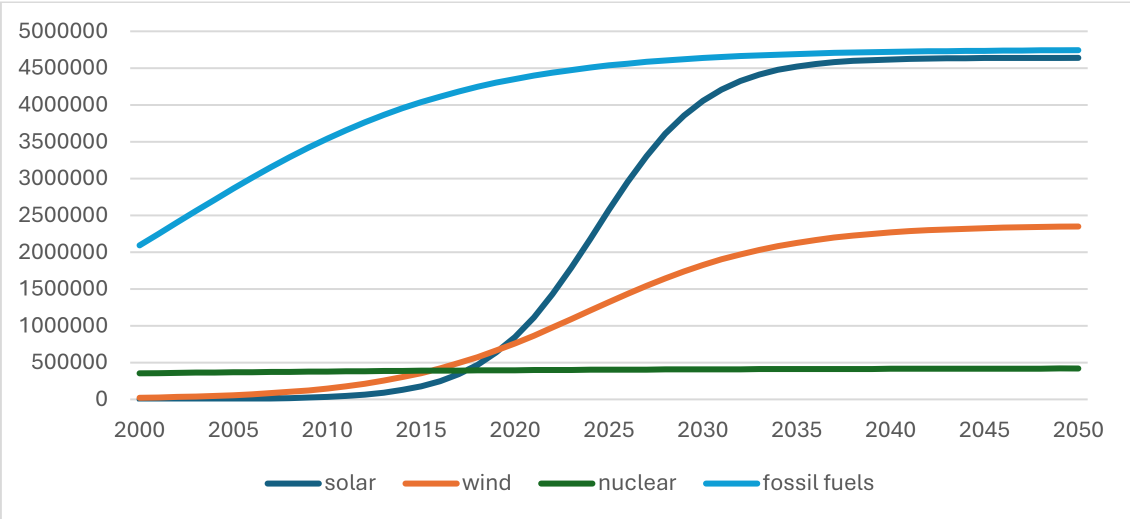


Figure 3: Projections for installed capacity (MW) of solar, wind, nuclear and fossil fuels from 2000 to 2050

Source: Own elaboration

As explained in the methods section, the insufficient data hindered the projection of energy consumption by source. However, projections of total energy consumption, in 2050, point to 176388.89 TWh, which implies that the share of electricity generation within total energy consumption is anticipated to be 33.08% by 2050. This further confirms the ongoing electrification of the energy sector, crucial to achieving net zero emissions. A preposition that holds when the same model is applied to forecast electricity generation by source (see Figure 4), the logistic regression model projects that by 2050, solar energy will constitute the largest share of electricity generation (37.4%), followed by wind (21.2%), fossil fuels (18.5%) and nuclear (7.6%).

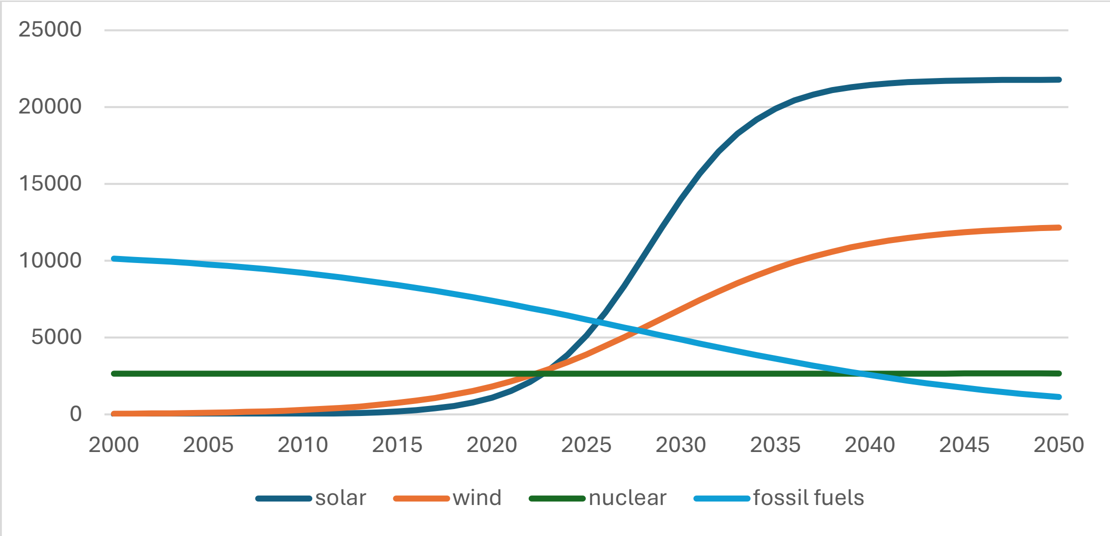


Figure 4: Projections for electricity generation (MW) per energy source from 2000 to 2050

Source: Own elaboration

However, one should point out that the accuracy of these predictions is very much contingent on external variables such as technological advancements, policy incentives and environmental concerns which may influence the rate of transition.

## 5. Discussion

The logistic diffusion model employed in this study explains the cumulative adoption of technologies over time by using time itself as a key variable, which, while useful for descriptive and predictive purposes, does not delve into the underlying mechanisms driving diffusion, such as policy and market dynamics, structural shifts and cost reductions.

To address this gap, it is essential to contextualize the diffusion process within the economic factors identified earlier in this study, namely the levelized cost of electricity (LCOE), learning curves, energy-GDP and electricity-GDP elasticities and the diffusion indicators. Through these, we can move beyond the descriptive nature of the logistic model and provide a more nuanced explanation of the diffusion process.

### Policy and market dynamics

The analysis of historical trends (Section 2.2.1 and 2.2.2) highlights the importance of policy incentives, such as feed-in tariffs and subsidies, in driving the adoption of renewable energy technologies. For example, the rapid growth of solar PV in Germany following the introduction of the Renewable Energy Law (EEG) in 2000 demonstrates how policy interventions can accelerate the diffusion of new technologies.

Similarly, market dynamics, such as the availability of financing, play a critical role in determining the rate of technology adoption. For instance, the high correlation between installed capacity and electricity generation (0.985) suggests that investments in renewable energy infrastructure are directly translating into increased electricity output. Still, this correlation assumes continuous investment, which may not hold in contexts where political shifts lead to subsidy cuts or fossil fuel lobbying undermines renewable energy policies.

**Structural shifts**

Renewable energy adoption is not solely a function of technological feasibility but also of economic development stages and industrial composition. As economies transition from energy-intensive industries to service-oriented sectors, electricity consumption becomes increasingly central to economic activity. This shift creates a favourable environment for the diffusion of renewable energy technologies, particularly solar and wind, which are well-suited to meet the rising demand for electricity.

Therefore, by incorporating the energy-GDP and electricity-GDP elasticities into the analysis, we can better understand how macroeconomic trends influence the adoption of renewables. Overall, the results (see section 4.1) confirm that economic growth is becoming increasingly decoupled from total energy consumption, particularly in high-income countries, suggesting improvements in energy efficiency. Moreover, the higher electricity-GDP elasticities relative to overall energy-GDP elasticities support the hypothesis that economic development is increasingly tied to electricity consumption, corroborating evidence of a global shift toward electrification.

**Cost reductions**

The analysis also revealed that renewable energy technologies, particularly solar photovoltaics (PV) and onshore wind, exhibit strong learning effects, with cost reductions closely tied to cumulative installed capacity (see section 4.2). This cost reduction is a critical factor in accelerating the adoption of renewables, as it enhances their economic competitiveness relative to fossil fuels.

Learning curves, which quantify cost reductions per doubling of cumulative capacity, reveal a self-reinforcing cycle: early adoption driven by policy incentives (e.g. Germany's EEG) triggers economies of scale and technological refinement, further lowering costs and expanding the pool of potential adopters.

This dynamic aligns with the logistic model's rapid growth phase but adds explanatory depth: the inflection point of the S-curve corresponds to the threshold where renewables achieve grid parity with fossil fuels. In upper-middle-income nations, where energy demand grows in tandem with GDP (energy-GDP elasticity = 0.727), cost-competitive renewables displace marginal fossil fuel projects, accelerating adoption. Conversely, in low-income countries (energy-GDP elasticity = 0.142), weak institutional frameworks and reliance on non-commercial energy sources decouple cost reductions from adoption rates, underscoring that learning curves alone cannot drive diffusion without complementary infrastructure and financing.

## 6. Conclusion

This dissertation examines the historical decline in renewable energy costs relative to non-renewables, the evolution of their diffusion rates and the projected timeframe for renewables to surpass fossil fuels.

The analysis reveals that both solar and wind experience robust learning effects, particularly solar PV and onshore wind which exhibit the highest learning rates: 38.5% and 43.7%, respectively, between 2000 and 2023. In contrast, fossil fuels and nuclear power face cost stagnation due to regulatory burdens, fuel price volatility and diminishing efficiency gains.

Logistic regression models reveal that solar and wind adoption exhibit distinct S-curve patterns. Based on current trends and scenario assumptions, solar adoption is projected to approach saturation around 2035, while wind is expected to continue growing more gradually, stabilizing closer to 2050.

By mid-century, renewables are expected to account for 58.6% of global electricity generation, displacing fossil fuels (18.5%) as the primary energy source. Nuclear energy, while stable, shows limited growth potential due to high capital costs and public scepticism.

The findings also align with the broader trend of electrification, as evidenced by the higher electricity-GDP elasticity (1.002) relative to total energy-GDP elasticity (0.674) and the projected share of electricity generation within total energy consumption from 17.13% in 2023 to 33.08 in 2050.

While this study provides valuable insights into renewable energy diffusion, several limitations must be acknowledged. First, the reliance on historical data and static assumptions restricts the model's ability to account for political and regulatory variability. For instance, it does not fully capture the potential slowdown in renewable adoption due to policy reversals, such as the U.S. withdrawal from the Paris Agreement, or the accelerated deployment driven by crisis-responsive measures, exemplified by the EU's REPowerEU plan following the 2022 energy crisis.

A further limitation lies in the model's inability to adequately address regional disparities in renewable energy adoption. Low-income nations, characterized by an energy-GDP elasticity of 0.142, encounter distinct barriers, including underdeveloped grid infrastructure and persistent reliance on traditional biofuels, that are not explicitly incorporated into the logistic regression framework. Moreover, the study's focus on established technologies, such as solar and wind, leaves room for future research to explore emerging alternatives like green hydrogen and small modular reactors (SMRs), which could significantly alter diffusion trajectories if technological or policy breakthroughs occur.

To address these limitations, future research should incorporate dynamic modelling techniques, such as policy-sensitive scenario analysis, to better account for external shocks and regional differentiation, as it could enhance the predictive robustness and provide more nuanced insights into the heterogeneous adoption pathways.

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# Appendix

Annex I – Evolution of global GDP and GDP by income group from 2000 to 2023, at 2015 constant prices

| GDP (constant 2015 US$) | World | High income | Upper middle income | Lower middle income | Low income |
|---|---|---|---|---|---|
| **2000** | 48437263200388.00 | 37837833221211.70 | 8023928182257.55 | 2175258755731.17 | 232384864913.51 |
| **2001** | 49422295421127.10 | 38440956467142.00 | 8298389313935.03 | 2269776849002.72 | 242294958385.81 |
| **2002** | 50567138353080.40 | 39070505434255.10 | 8695783409550.23 | 2372218522706.63 | 254230951863.89 |
| **2003** | 52131518187621.40 | 39965854193436.40 | 9206218057715.95 | 2513317985219.06 | 266652967070.58 |
| **2004** | 54463866515800.90 | 41373496628592.40 | 9928782901497.89 | 2691342310908.53 | 283018908311.18 |
| **2005** | 56653579443885.40 | 42612340617051.00 | 10673460291074.30 | 2871957743475.89 | 301600732185.80 |
| **2006** | 59180664984371.90 | 43995708323418.20 | 11590864671935.00 | 3071996520794.39 | 319425410003.36 |
| **2007** | 61768752251196.40 | 45252860738753.20 | 12681834072559.20 | 3283873630647.52 | 338990131399.52 |
| **2008** | 63038812186080.80 | 45555784266220.70 | 13476120643095.90 | 3434574180396.17 | 357761842735.53 |
| **2009** | 62192598074458.60 | 44026249709201.90 | 13943259670108.70 | 3639196057719.62 | 372577449527.85 |
| **2010** | 65002105448721.20 | 45362091739586.70 | 15131983239721.80 | 3888776335478.37 | 398590989534.17 |
| **2011** | 67170761718394.30 | 46285169329733.40 | 16181405842624.50 | 4073797174037.51 | 401750791323.72 |
| **2012** | 68978972328520.30 | 46956278753190.40 | 17113469632028.40 | 4284201082472.95 | 389086119099.63 |
| **2013** | 70960627147647.50 | 47710588295439.20 | 18076729826774.40 | 4527485766916.12 | 403083436691.90 |
| **2014** | 73182741848317.40 | 48735210498279.80 | 18971909576956.90 | 4804501648342.21 | 420838437954.12 |
| **2015** | 75472473882835.10 | 49875503824325.00 | 19830615812257.50 | 5089665684079.03 | 417756953873.85 |
| **2016** | 77596070030857.20 | 50785141188183.50 | 20738282956924.50 | 5379808124885.27 | 426318507337.12 |
| **2017** | 80274256581671.90 | 52036148520657.30 | 21848798125044.00 | 5673767311022.84 | 439594337732.54 |
| **2018** | 82909015820695.80 | 53266571470321.40 | 22920245490506.70 | 5982516241313.00 | 454537993853.64 |
| **2019** | 85127633137500.80 | 54281884301810.90 | 23852451210920.70 | 6226615757545.93 | 474081737618.70 |
| **2020** | 82677384726296.40 | 52182339286318.70 | 23733210553042.70 | 6002516344310.31 | 475602794987.66 |
| **2021** | 87927472715845.20 | 55197692751535.10 | 25538815903716.60 | 6402342783987.56 | 485946125646.54 |
| **2022** | 90774582977538.80 | 56797832930107.10 | 26384548095052.60 | 6775936832420.70 | 503780277751.38 |
| **2023** | 93346688686736.90 | 57808823390117.10 | 27548975484262.30 | 7151756621411.38 | 515060189857.05 |

| Compound annual growth rate (%) | 2.77 | 1.78 | 5.27 | 5.08 | 3.37 |
|---|---|---|---|---|---|

Source: WORLD BANK

Annex II – Evolution of global energy consumption and by income group from 2000 to 2023

| Energy consumption (TWh) | World | High income | Upper middle income | Lower middle income | Low income |
|---|---|---|---|---|---|
| **2000** | 110368.06 | 66301.102 | 31123.891 | 9483.466 | 770.864 |
| **2001** | 111445.56 | 66167.211 | 32031.521 | 9668.767 | 778.333 |
| **2002** | 113809.49 | 66807.82 | 33323.055 | 10014.536 | 797.918 |
| **2003** | 117810.22 | 67543.156 | 36182.387 | 10300.468 | 811.401 |
| **2004** | 123728.97 | 69031.711 | 39725.801 | 11025.695 | 867.02 |
| **2005** | 127874.88 | 69606.219 | 42661.27 | 11530.44 | 921.059 |
| **2006** | 131488.69 | 69791.578 | 45546.965 | 12002.561 | 939.351 |
| **2007** | 135522.59 | 70379.82 | 48205.031 | 12735.961 | 954.002 |
| **2008** | 137130.72 | 69905.258 | 49710.469 | 13220.371 | 996.973 |
| **2009** | 134952.47 | 66725.516 | 50367.715 | 13558.873 | 975.779 |
| **2010** | 141457.53 | 69548.258 | 53312.188 | 14106.84 | 1010.112 |
| **2011** | 144707.94 | 68926 | 56549.184 | 14787.825 | 944.45 |
| **2012** | 146744.78 | 68449.938 | 58551.512 | 15226.531 | 885.968 |
| **2013** | 149299.22 | 69288.477 | 59745.57 | 15650.51 | 854.95 |
| **2014** | 150891.02 | 68968.297 | 60937.973 | 16286.321 | 856.591 |
| **2015** | 152035.48 | 69428.344 | 61171.875 | 16584.59 | 796.135 |
| **2016** | 153607.73 | 69772.227 | 61821.645 | 17025.846 | 830.969 |
| **2017** | 157252.06 | 70310.633 | 63656.918 | 17980.84 | 828.593 |
| **2018** | 161518.44 | 71208.969 | 65905.977 | 18865.455 | 861.4 |
| **2019** | 163346.59 | 70417.383 | 67898.992 | 19437.158 | 872.842 |
| **2020** | 157667.72 | 65687.578 | 67782.734 | 18813.914 | 837.249 |
| **2021** | 165729.03 | 68638.273 | 71423.508 | 19882.926 | 856.518 |
| **2022** | 168708.2 | 65800.93 | 73540.633 | 20341.938 | n.d |

| | | | | | |
|---|---|---|---|---|---|
| **2023** | 172119.06 | 64908.398 | 76803.555 | 21152.625 | n.d |
| **CAGR (%)** | 1.87 | -0.09 | 3.84 | 3.93 | 0.48 |

Source: OUR WORLD IN DATA

Table III – Evolution of global electricity generation and by income group from 2000 to 2023

| **Electricity generation (TWh)** | **World** | **High income** | **Upper middle income** | **Lower middle income** | **Low income** |
|---|---|---|---|---|---|
| **2000** | 15276.96 | 9854.73 | 4015.83 | 1326.6 | 75.04 |
| **2001** | 15499.4 | 9867.42 | 4165.55 | 1380.75 | 80.45 |
| **2002** | 16049.01 | 10104.74 | 4409.11 | 1446.57 | 83.16 |
| **2003** | 16626.6 | 10228.46 | 4780.25 | 1525.57 | 86.6 |
| **2004** | 17412.81 | 10470.1 | 5209.07 | 1635.54 | 92.15 |
| **2005** | 18132.8 | 10722.811 | 5610.57 | 1692.9 | 100.39 |
| **2006** | 18838.11 | 10818.47 | 6119.89 | 1788.76 | 104.65 |
| **2007** | 19712.15 | 11072.05 | 6651.24 | 1873.82 | 108.55 |
| **2008** | 20099.89 | 11079.05 | 6967.22 | 1934.21 | 112.76 |
| **2009** | 19941.4 | 10678.95 | 7134.4 | 2002.14 | 119.1 |
| **2010** | 21263.27 | 11142.86 | 7830.93 | 2155.14 | 127.25 |
| **2011** | 21957.08 | 11101.39 | 8425.42 | 2302.62 | 120.58 |
| **2012** | 22515.84 | 11129.7 | 8825.43 | 2439.19 | 114.28 |
| **2013** | 23155.39 | 11139.32 | 9353.819 | 2542.76 | 112.22 |
| **2014** | 23749.42 | 11144.08 | 9769.931 | 2716.18 | 111.93 |
| **2015** | 24005.79 | 11214.76 | 9851.9 | 2821.81 | 109.92 |
| **2016** | 24662.78 | 11298.64 | 10250.681 | 2986.11 | 119.9 |
| **2017** | 25403.15 | 11374.271 | 10771.45 | 3129.53 | 120.44 |
| **2018** | 26399.83 | 11525.91 | 11436.75 | 3305.71 | 124.09 |
| **2019** | 26771.23 | 11421.41 | 11811.49 | 3405.77 | 125.06 |
| **2020** | 26654.82 | 11152.55 | 11970.141 | 3397.65 | 126.28 |
| **2021** | 28169.88 | 11476.71 | 12931.12 | 3625.91 | 128.65 |

| | | | | | |
|---|---|---|---|---|---|
| **2022** | 28843.5 | 11594.29 | 13341.23 | 3774.11 | 126.35 |
| **2023** | 29479.05 | | | | |
| **CAGR (%)** | 2.78 | 0.71 | 5.36 | 4.65 | 2.29 |

Source: OUR WORLD IN DATA

Annex IV – Levelized cost of electricity by energy source from 2010-2023

| **Levelised cost of electricity (2023 USD/kWh)** | **Concentrated Solar Power (CSP)** | **Solar PV** | **Onshore Wind** | **Offshore Wind** | **Oil** | **Combined Cycle Gas Turbine (CCGT)** | **Coal** | **Open Cycle GasTurbine (OCGT)** |
|---|---|---|---|---|---|---|---|---|
| **2010** | 0.393 | 0.460 | 0.111 | 0.203 | 0.360 | 0.107 | 0.104 | 0.269 |
| **2011** | 0.381 | 0.343 | 0.106 | 0.212 | 0.389 | 0.130 | 0.111 | 0.297 |
| **2012** | 0.358 | 0.256 | 0.096 | 0.179 | 0.388 | 0.137 | 0.105 | 0.324 |
| **2013** | 0.292 | 0.197 | 0.097 | 0.153 | 0.395 | 0.143 | 0.098 | 0.327 |
| **2014** | 0.256 | 0.177 | 0.086 | 0.186 | 0.386 | 0.135 | 0.093 | 0.300 |
| **2015** | 0.246 | 0.132 | 0.074 | 0.152 | 0.302 | 0.104 | 0.091 | 0.256 |
| **2016** | 0.291 | 0.116 | 0.069 | 0.124 | 0.292 | 0.082 | 0.092 | 0.225 |
| **2017** | 0.278 | 0.091 | 0.065 | 0.115 | 0.306 | 0.090 | 0.099 | 0.238 |
| **2018** | 0.164 | 0.077 | 0.055 | 0.108 | 0.334 | 0.100 | 0.108 | 0.252 |
| **2019** | 0.242 | 0.067 | 0.048 | 0.093 | 0.318 | 0.091 | 0.104 | 0.235 |
| **2020** | 0.122 | 0.060 | 0.040 | 0.088 | 0.284 | 0.077 | 0.101 | 0.218 |
| **2021** | 0.124 | 0.052 | 0.036 | 0.080 | 0.339 | 0.115 | 0.121 | 0.273 |
| **2022** | 0.122 | 0.050 | 0.034 | 0.080 | 0.389 | 0.187 | 0.160 | 0.371 |
| **2023** | 0.117 | 0.044 | 0.033 | 0.075 | 0.357 | 0.121 | 0.134 | 0.269 |
| **CAGR (%)** | -8.28 | -15.40 | -8.36 | -6.89 | -0.07 | 0.85 | 1.86 | -0.01 |

Source: Renewable Power Generation Costs in 2023, IRENA

Annex V – Evolution of energy consumption by energy source from 2000-2023

| **Energy comsumption (TWh)** | **Total** | **Coal** | **Gas** | **Oil** | **Nuclear** | **Solar** | **Wind** |
|---|---|---|---|---|---|---|---|
| **2000** | 110368.1 | 27441.49 | 23994.26 | 42983.430 | 7322.683 | 3.129 | 92.878 |
| **2001** | 111445.6 | 27864.72 | 24316.83 | 43366.160 | 7480.557 | 4.178 | 112.752 |
| **2002** | 113809.5 | 28967.59 | 25028.29 | 43650.73 | 7551.077 | 5.246 | 152.894 |
| **2003** | 117810.2 | 31511.33 | 25727.73 | 44580.05 | 7350.656 | 6.534 | 183.533 |
| **2004** | 123729 | 33689.84 | 26734.27 | 46367.14 | 7635.77 | 8.555 | 246.722 |
| **2005** | 127874.9 | 36190.77 | 27438.98 | 46965.55 | 7607.354 | 11.978 | 299.591 |
| **2006** | 131488.7 | 38073.16 | 28161.39 | 47468.77 | 7653.722 | 16.379 | 379.87 |
| **2007** | 135522.6 | 40233.9 | 29315.7 | 48022.76 | 7450.836 | 22.077 | 484.949 |
| **2008** | 137130.7 | 40786.05 | 30026.69 | 47628.99 | 7381.602 | 35.639 | 622.182 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **2009** | 134952.5 | 40189.99 | 29405.7 | 46566.07 | 7232.23 | 58.819 | 773.015 |
| **2010** | 141457.5 | 41988.31 | 31593.82 | 48058.23 | 7373.091 | 94.092 | 961.486 |
| **2011** | 144707.9 | 43940.8 | 32349.12 | 48400.32 | 7021.486 | 181.254 | 1215.681 |
| **2012** | 146744.8 | 44061 | 33203.14 | 49164.34 | 6500.369 | 278.349 | 1454.615 |
| **2013** | 149299.2 | 44709.24 | 33720.78 | 49654.36 | 6512.807 | 377.791 | 1732.055 |
| **2014** | 150891 | 44893.17 | 33961.7 | 50011.83 | 6606.008 | 534.491 | 1912.332 |
| **2015** | 152035.5 | 43680.5 | 34752.11 | 50977.21 | 6655.106 | 689.423 | 2238.73 |
| **2016** | 153607.7 | 42736.86 | 35229.35 | 52060.85 | 6714.155 | 879.125 | 2575.674 |
| **2017** | 157252.1 | 43193.28 | 36517.57 | 52978.8 | 6734.279 | 1185.098 | 3038.975 |
| **2018** | 161518.4 | 43852.79 | 38321.44 | 53521.39 | 6855.408 | 1520.514 | 3361.329 |
| **2019** | 163346.6 | 43597.16 | 39084.45 | 53618.93 | 7071.782 | 1859.597 | 3746.709 |
| **2020** | 157667.7 | 42296.68 | 38714.09 | 48745.68 | 6776.866 | 2245.268 | 4188.111 |
| **2021** | 165729 | 44600.08 | 40239.02 | 51530.49 | 7037.07 | 2751.753 | 4865.935 |
| **2022** | 168708.2 | 44869.12 | 40086.88 | 53226.84 | 6703.874 | 3446.407 | 5495.744 |
| **2023** | 172119.1 | 45564.93 | 40101.74 | 54564 | 6824.177 | 4264.261 | 6040.359 |
| **CAGR (%)** | 1.87 | 2.14 | 2.16 | 0.99 | -0.29 | 35.08 | 19.00 |

Source: OUR WORLD IN DATA

Annex VI – Evolution of electricity generation by energy source from 2000-2023

| **Electricity generation (TWh)** | **Total** | **Coal** | **Gas** | **Oil** | **Nuclear** | **Solar** | **Wind** |
|---|---|---|---|---|---|---|---|
| **2000** | 15276.96 | 5809.34 | 2745.09 | 1323.67 | 2540.46 | 1.03 | 31.14 |
| **2001** | 15499.4 | 5891.62 | 2914.23 | 1284.41 | 2613.17 | 1.37 | 38.17 |
| **2002** | 16049.01 | 6145.74 | 3104.36 | 1270.87 | 2654.78 | 1.71 | 52.21 |
| **2003** | 16626.6 | 6576.3 | 3255.04 | 1294.96 | 2601.05 | 2.1 | 63.18 |
| **2004** | 17412.81 | 6798.53 | 3503.85 | 1261.86 | 2719.41 | 2.78 | 85.45 |
| **2005** | 18132.8 | 7168.54 | 3679.83 | 1277.95 | 2726.97 | 3.95 | 104.37 |
| **2006** | 18838.11 | 7568.05 | 3901.44 | 1174.57 | 2761.59 | 5.42 | 133.16 |
| **2007** | 19712.15 | 8052.88 | 4220.48 | 1194.83 | 2703.49 | 7.29 | 171.11 |
| **2008** | 20099.89 | 8075.56 | 4361.83 | 1169.65 | 2694.72 | 11.85 | 220.8 |
| **2009** | 19941.4 | 7952.25 | 4383.28 | 1069.87 | 2656.76 | 19.82 | 276.21 |
| **2010** | 21263.27 | 8459.82 | 4816.71 | 1069.2 | 2725.91 | 32.2 | 345.92 |
| **2011** | 21957.08 | 8913.04 | 4864.28 | 1175.29 | 2610.34 | 63.58 | 439.88 |
| **2012** | 22515.84 | 8962.88 | 5172.06 | 1227.52 | 2432.22 | 96.99 | 529.18 |
| **2013** | 23155.39 | 9426.88 | 5073.84 | 1180.35 | 2448.52 | 131.96 | 634.05 |
| **2014** | 23749.42 | 9607.3 | 5237 | 1120.83 | 2498.73 | 197.74 | 706.01 |
| **2015** | 24005.79 | 9281.27 | 5553.96 | 1118.41 | 2532.93 | 256 | 829.57 |
| **2016** | 24662.78 | 9332.96 | 5839.46 | 1060.76 | 2571.05 | 328.11 | 960 |
| **2017** | 25403.15 | 9628.8 | 5958.21 | 987.45 | 2594.23 | 445.37 | 1138.96 |
| **2018** | 26399.83 | 10008.43 | 6197 | 888.57 | 2658.7 | 575.12 | 1267.89 |
| **2019** | 26771.23 | 9802.03 | 6369.66 | 834.83 | 2754.08 | 705.52 | 1419.8 |
| **2020** | 26654.82 | 9417.44 | 6332.21 | 773 | 2648.37 | 853.37 | 1590.68 |
| **2021** | 28169.88 | 10156.81 | 6492.94 | 830.76 | 2762.24 | 1055.68 | 1849.47 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **2022** | 28843.5 | 10288.29 | 6581.64 | 849.26 | 2639.68 | 1323.32 | 2098.52 |
| **2023** | 29479.05 | 10467.93 | 6622.93 | 788.55 | 2685.74 | 1629.9 | 2304.44 |
| **CAGR (%)** | 2.78 | 2.48 | 3.74 | -2.14 | 0.23 | 35.93 | 19.64 |

Source: OUR WORLD IN DATA

Annex VII – Evolution of cumulative installed capacity per energy source from 2000 to 2023

| **Installed capacity (MW)** | **Solar** | **Wind** | **Nuclear** | **Fossil Fuels** |
|---|---|---|---|---|
| **2000** | 1215.680 | 16963.68 | 358461.5 | 2289991 |
| **2001** | 1465.532 | 23958.91 | 360322.4 | 2313301 |
| **2002** | 1810.799 | 30724.98 | 366680.5 | 2434129 |
| **2003** | 2334.37 | 38664.06 | 366526.4 | 2554781 |
| **2004** | 3418.521 | 47659.21 | 373804.6 | 2634710 |
| **2005** | 4925.005 | 58467.66 | 377973.5 | 2732706 |
| **2006** | 6475.283 | 73147.61 | 378598.3 | 2869234 |
| **2007** | 8947.762 | 91520.79 | 379782.2 | 2991439 |
| **2008** | 15215.49 | 115535.2 | 378601.6 | 3093843 |
| **2009** | 23536.86 | 150103 | 379947.4 | 3207016 |
| **2010** | 41530.93 | 181060.7 | 381693.9 | 3351854 |
| **2011** | 72820 | 220199.2 | 386417.3 | 3475527 |
| **2012** | 103027.9 | 267310 | 378876.7 | 3584325 |
| **2013** | 140208.5 | 299928.6 | 376876.8 | 3692805 |
| **2014** | 179631.5 | 349458.1 | 383714.8 | 3818631 |
| **2015** | 228073.8 | 416435.1 | 383390.5 | 3909853 |
| **2016** | 300137.7 | 467240.8 | 398320.3 | 4004451 |
| **2017** | 395846.2 | 514930.3 | 398748.9 | 4094480 |
| **2018** | 491980.2 | 563680.1 | 405197.7 | 4217789 |
| **2019** | 595019.6 | 622730.3 | 403681.8 | 4271415 |
| **2020** | 726221.4 | 733472.5 | 398902.4 | 4337977 |
| **2021** | 870635 | 824320.9 | 401077.9 | 4397545 |

| | | | | |
|---|---|---|---|---|
| **2022** | 1070843 | 902883.4 | 399757.4 | 4452038 |
| **2023** | 1418008 | 1017390 | 397807.1 | 4528065 |
| **CAGR (%)** | 34.21 | 18.59 | 0.43 | 2.88 |

Source: Renewable Energy Statistics in 2023, IRENA