Experience curve models in technology cost forecasting: The case of solar Photovoltaic modules

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Abstract

Energy technology models are required to enable strategic plans for decarbonisation. This requires accurate modelling of cost reductions due to technological learning. The premise of this research is to determine if new experience curve models could be implemented to reduce the error in cost estimates for solar PV technologies.

Experience curves are used in technology cost models, where technology costs decline as experience is gained through production and implementation. Since Wright's observation of the phenomenon in 1936, experience curves have been conventionally written as a linear function of cost and production, assuming constant learning over time.

This research investigates the constant learning rate by evaluating the experience curve slope in relation to the shape of the model. It compares conventional (linear) and contemporary (nonlinear) experience curve functional forms to determine the most accurate model.

The application of nonlinear experience curve models, that mathematically allow for a flattening effect, is not well explored in literature on emerging technologies in general, and energy technologies to our knowledge. Simplicity and ease of use are among reasons of the popularity of conventional models.

The purpose of this research is to investigate the reliability of contemporary experience curve models in forecasting technological cost compared to Wright's conventional model. This analysis specifically examines whether the implementation of Gompertz and the Logistic nonlinear models would reduce the error in cost estimates in comparison to Wright's power-law curve. It is a detailed theoretical and statistical review on the performance of these models in the analysis of technological learning. The statistical comparison is performed using global Solar Photovoltaic (PV) modules production data.

By conducting a regression analysis, the results showed a statistically significant reduction in error in nonlinear models through the measurement the two error terms, Sum of Squared Errors and Mean Absolute Percent Error. This thesis explains in detail how testing was conducted to compare the different experience curve methodologies, using 25 years production data for solar PV modules cumulative installed capacity and inflation-adjusted costs. The research further justifies the theoretical necessity for models that explain the diminishing technological learning rates. It is acknowledged that, in addition to technological progress, addressing global challenges through innovation also involves social, political and economic changes.

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Acronyms

ANOVA – Analysis Of Variance

APE – Absolute Percent Error

BOS – Balance of System

CAGR - Compound annual growth rate

CPI – Consumer Price Index

FRED - Federal Reserve Economic Data

GDP – Gross Domestic Product

GNP – Gross National Product

LR – Learning Rate

MAD – Mean Absolute Deviation

MAE – Mean Absolute Error

MAPE – Mean Absolute Percent Error

MW – Megawatts

MFEC – Multi Factor Experience Curve

NLS – Nonlinear Least Squares

NW – Newey-West test

OLS – Ordinary Least Squares

PR – Progress Ratio

PV - Photovoltaic

RMSE – Root Mean Squared Error

SFEC – Single Factor Experience Curve

SSE – Sum of Squared Error

SW – Shapiro-Wilk test for normality

To my late father whom, 12 years later, I miss more than ever.

Acknowledgments

I would like to express my sincere appreciation to my lead supervisor, Dr. Rob Hayward, for his encouragement, support, and guidance throughout the course of this thesis effort. I am also grateful to my supervisor, Dr. Timothy Laing, who has helped me during my work. The insight and experience were certainly appreciated.

Declaration

I declare that the research contained in this thesis, unless otherwise formally indicated within the text, is the original work of the author. The thesis has not been previously submitted to this or any other university for a degree, and does not incorporate any material already submitted for a degree.

Bdour Sbeih

31/01/2023

Chapter One: Introduction

1.1 Background

It is widely accepted that technological innovation is an important driver of economic growth of countries and regions. The importance of innovations for social change, global competitiveness, and productivity has been thoroughly analysed in recent decades in economic studies. Economic criteria determine the success of technological innovation based on various factors such as: market forces, the technology's characteristics, and acquired knowledge via technological learning. The intersection between Economics and innovation is where the successful transformation of an idea into a commercial product occurs.

That been said, information on the economic impact of technological innovation has always been valuable for management to make better decisions regarding strategic planning, Research and Development (R&D) management, product development and competitiveness, and so forth. Therefore, several mechanisms have been proposed to explain technological innovation links with the market (Adler & Clark, 1991; Nemet, 2006). In this respect, technological forecasting provided context to understand the economics of innovation – the relatively new branch of economics that focuses on the study of technology, science, society and business:

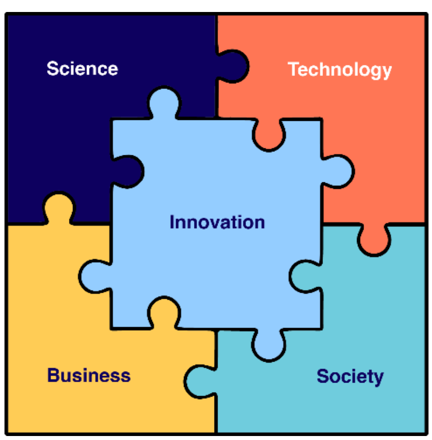

Figure 1.1: Economics of innovation matrix

Cost is one of the most important economic measures of success for new technologies. Projecting technology performance and cost has been improving over the years (Walk, 2012). Historically, technological change has been predicted following various qualitative and quantitative approaches. Qualitative approaches mainly depend on expert opinions and consensus as seen in the Delphi method for example[1]. These methods, however, were of limited usefulness due to its impracticality, being hard to replicate and the possibility of experts' bias. In consequence, reliable quantitative forecasting methods have been developed that project the growth, diffusion, and the cost of technology over time (e.g.: projecting technology substitutions, saturation levels, and performance improvements) (Walk, 2012).

One of the well-established quantitative methods is based on the concept of experience curves. The theory behind the experience curves consists of the conceptualisation of the technological change process at some of its aspects: cost and technological learning. Technological cost reduction, due to technological learning, is embodied mathematically in the form of ***experience curves model***, which are often used to predict and understand the long-term patterns of technological cost. Using a classical econometric model, the experience effect is measured in terms of reduction in the *unit cost of a product* as a function of the increase in its output at a certain time. As the technology is developed, accumulated learning due to accumulated capacity makes a technology to have a cost reduction pattern in production.

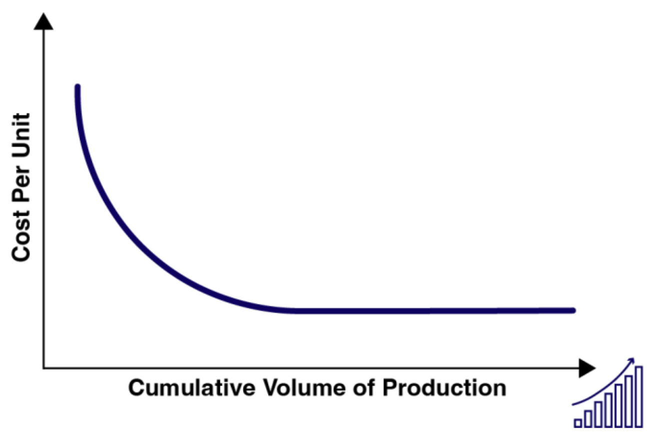

Figure 1.2: Graphical representation of the experience curve phenomenon

[1] More details on qualitative forecasting and the Delphi method can be found in Chapter Two.

The first use of the experience curve in economic studies is attributed to T. P. Wright (1936) in his famous paper on aircraft production. Since Wright's observation of the phenomenon, experience curves were frequently proposed as a distinct quantification of technological learning; the key phenomenon that determines the future cost of technologies.

Over the years, Wright's original model has undergone numerous conceptual and methodological variations to evolve into the widely accepted model used today. However, most researchers agreed that correlating improvements in performance (acquired through learning by doing, skills, efficiency, and scale) to cumulative production, and expressing the correlations in a mathematical model provide a phenomenological starting point in many industries (Arrow, 1962; Alchian, 1963; Baloff, 1966; BCG, 1972; Goddard, 1982; McDonald, 2001; Day and Montgomery, 1983; Englmann, 1994; Neij, 1997; Reati, 1998; Nordhaus, 2014; Rypdal, 2018; Nagy, Hansen 2018). The basic architecture of Wright's model is:

$$y = ax^{-b} \tag{1.1}$$

In this model, y represents the estimated production cost for the x^{th} unit produced where a is the production cost of the theoretical first unit produced, and b is a factor of the learning rate which will be explained in greater detail in Chapter Three, the Theoretical Literature Review.

That been said, sustainability and environmental issues, such as climate change, are global challenges that require a lot of innovative solutions now and in the future. Economic growth is expected to face a major threat at the global level as a result of global warming. Global warming is projected to increase by 1.5 °C between 2030 and 2052, which could affect public health, human security, and economic growth. The successful research, development, and deployment of new, responsible innovative technologies is a cornerstone of the transition towards a low-carbon economy. Such a fact has stimulated the development and deployment of new energy technologies to face the growing environmental concerns (Neij, 1997).

Despite the environmental benefits, economic factors are the most important drivers of growing renewable energy investments. The success of the renewable energy transition can be measured both by the level of cost reduction and the extent of market penetration of renewable technologies (Papineau, 2006). In the past three decades, cost reduction has been more than expected, when in fact market penetration has been markedly lower than expected (Darmstadter, 2000). Alas, the globe is still struggling to hit the climate emergency brake (Hussain et al., 2017; Koskinen, 2016). Global carbon emissions aren't falling fast enough, in fact, they bounced back up in 2021 in the United States according to Rhodium Group in Figure 1.3:

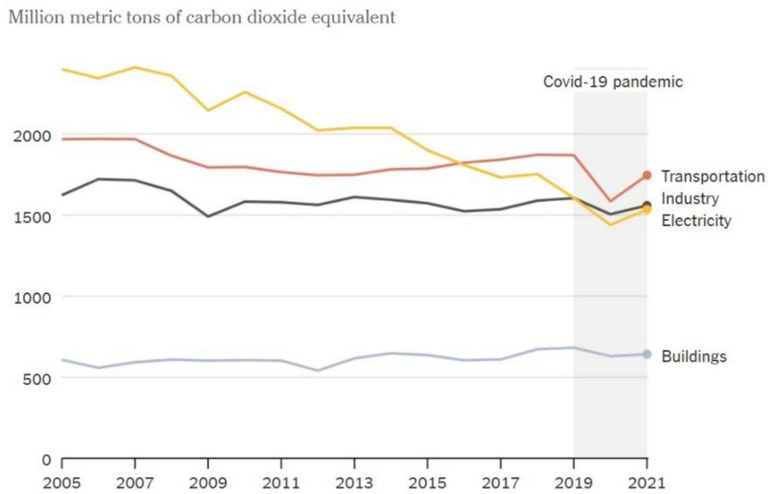

Figure 1.3: U.S. Greenhouse Gas Emission, By Sector. (Source: Rhodium Group by New York Times)

Additional deployment and adoption of renewable energy technologies requires further development and cost cutting through innovation and experience. However, the cost trajectories of emerging energy technologies are less certain than those of the conventional fossil fuel technologies. Overcoming the cost barriers of promising large-potential technologies, such as solar photovoltaic (PV) technologies, may require investing up to several hundred billion US dollars in learning to break-even with conventional energy systems.

Figure 1.4 shows how experience curves help determining the investment necessary to make a technology, such as solar PV, cost competitive. The curve, however, does not forecast when the technology will break-even. This time, the break-even time, depends on deployment rates, which can be influenced through research and development (R&D), price subsidies, and other forms of deployment policies (IEA, 2000):

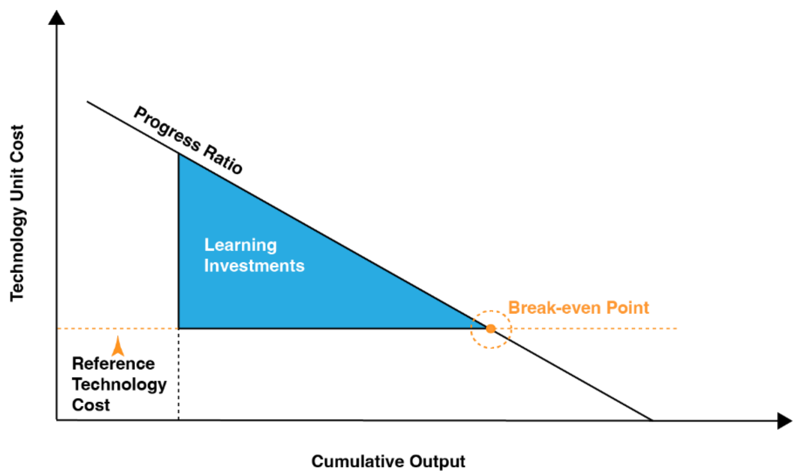

Figure 1.4: Required investments for renewable technologies to become cost competitive.

Understanding the long-term patterns of profitability in energy technologies is crucial for investment decisions and public policy planning in the context of climate change. These forecasts must be studied and applied at the early stages of projects planning to better predict future technology performance, assure the successful selection of new technology, and improve technology management overall (Arrow, 1962).

For long, technology deployment trajectories and cost competitiveness in energy systems have been discussed in scenarios published by international organisations (e.g., International Energy Agency; IEA), consultants (e.g., Bloomberg New Energy Finance; BNEF), and academia (e.g., MIT). However, scenario results are not projections of the future but a representation of possible developments based on internally consistent dynamics (IEA, 2000; Ioannis, 2018). As such, results are possibly affected by uncertain parameters such as macro-economic indicators, fossil fuel, technology development and policy changes. Therefore, newfound interest in experience curves has arisen recently as governments look for efficient plans to address climate change correctly. Yet, the focus has shifted to endogenous technical change and the estimate of reliable technological learning rates as inputs in energy forecasting models instead of production planning or strategic management (Papineau, 2006; Shukla et al., 2016; Alizadeh et al., 2020).

Researchers have focused on evaluating the process of cost reduction due to technological learning, which has led to the application of experience curve models to renewable energy technologies. With an experience curve, this thesis tries to analyse the cost reduction pattern of Solar Photovoltaic (PV) technologies, the most visible example of cost reduction in this context. It aims to study different possible geometric shapes of experience models to determine which one fits better for the future cost forecasting objectives.

Solar photovoltaic (PV) systems have come a long way in achieving high growth rates and installed capacity in different countries (Asante et al., 2020; Candelise et al., 2013; Chu, 2003; Rodrigues et al., 2016). The decline in solar PV modules cost, the main component in a solar energy system, has been the largest in modern history with 100-fold in the last forty years:

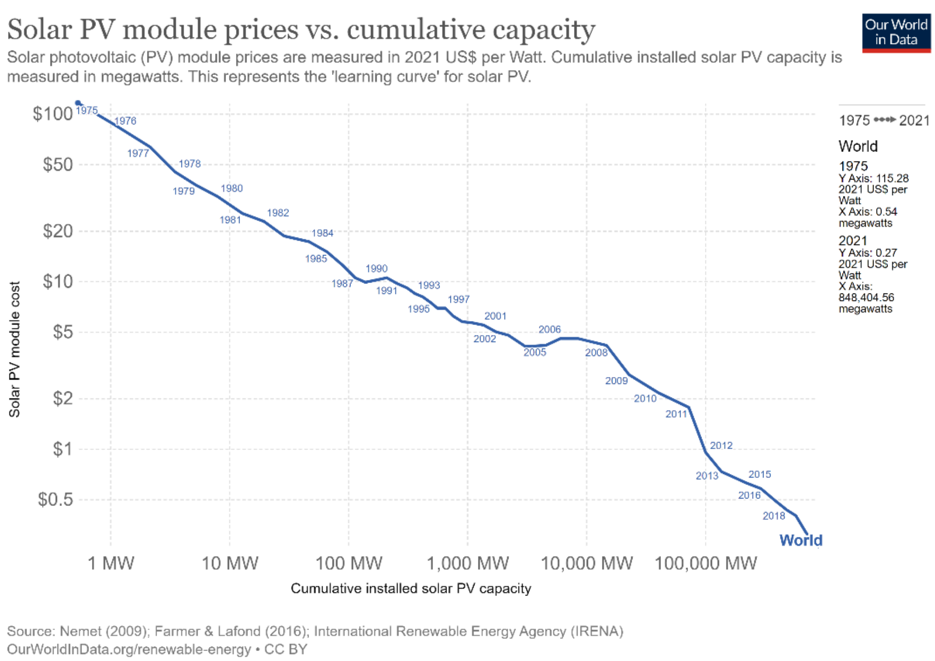

Figure 1.5: Global solar PV module prices ($/W) vs cumulative capacity (MW)

One of the reasons behind the strong presence of experience curve effect in the solar PV industry is the solar power cost determinants. The operating costs of solar power are comparatively low, and they don't pay for any fuel (Candelise et al., 2013; de La Tour et al., 2013). However, what determines the cost in such capital-intensive industry is the cost of solar PV technologies used (Chu, 2003; Eising et al., 2020; International Energy Agency, 2000; McDonald & Schrattenholzer, 2001; Wagner, 2014). Therefore, to understand why and how solar energy can become cost competitive, one must understand the reason why solar technologies get cheap and how. This should help decision makers understand the endogenous and exogenous factors that affect growth in the PV industry (e.g.: solar power intermittency, the need of land, faults that spark fires, feed-in-tariffs, aggressive competition with China, etc.).

According to the experience curve theory, explained further in Chapter Three, historical cost reduction of technologies has been correlated with their cumulative production or installed capacity based on a learning rate. In the case of photovoltaic (PV) this could be the capacity of modules produced and/or installed (Shukla et al., 2016; Ioannis, 2018). Studies on photovoltaic technology have proposed an approximate 20% of cost reduction for each doubling of the capacity output. This reduction can be mainly explained by one factor, or by two, or even more, making the model too complex (Muraleedharakurup et al., 2010)

The use of log-linear experience curves that relate reductions in the unit cost of clean energy technologies to their cumulative production, has become a common method of representing experience curves in energy-economic models. Yet, there are significant uncertainties in the linear model's formulation whose impact on key model results have been insufficiently examined or considered (Yeh & Rubin, 2012). The current experience curve model in use today mathematically states that as the cumulative quantity of units produced doubled, the cumulative average cost decreased at a constant rate (Wright, 1936; Yelle, 1979; Goddard, 1982) .

However, empirical research has early emphasised that technological learning is not constant (Carr, 1946; Alchian, 1963; Baloff, 1966; Henderson, 1984; Hall & Howell, 1985; McDonald & Schrattenholzer, 2001). Carr (1946), Alchian (1963) and Baloff (1966) were among the first who challenged linear experience curve models and their inherited constant learning rates. History shows that there is a flattening effect near the end of production runs, and technological learning does not remain constant. Therefore, a model that assumes constant learning may not be appropriate for accurate experience curve estimates. Researchers have demonstrated both theoretically and empirically that the effects of learning slow or cease over time:

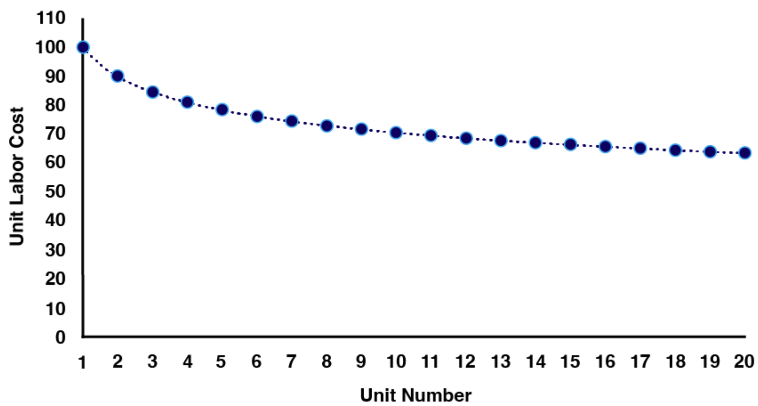

Figure 1.6: The effects of learning over time in a technology's life cycle

Applying the results of an experience curve estimation, when using inappropriate functional form, can create exaggerated cost reduction effects and, consequently, misleading results (Hogan et al., 2020). Fairly small uncertainties in experience curves proliferate to large uncertainties in estimates and, accordingly, cost competitiveness in the market (Neij, 1997). When estimating production runs, especially over longer periods of time, the conventional experience curve would likely underestimate the unit costs of those farthest out in the future (Yeh & Rubin, 2012). The underestimation would possibly occur because the model would estimate a constant learning rate, when in fact actual learning would diminish, causing the actuals to be higher than the estimate. The current experience curve could miss significantly on cost estimation; because a small error in the percentage of an estimate can still be large in terms of dollars (Johnson, 2016).

Figure 1.7 explains how different learning slope estimates result in a big differential cost for company A and company B, which incurs from choosing between alternatives (Henderson, 1984; Hall & Howell, 1985; Johnstone, 2015):

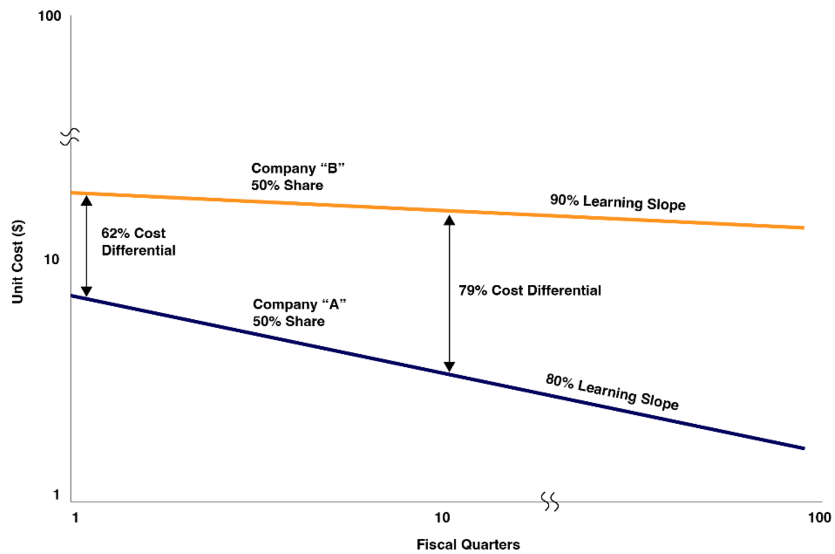

Figure 1.7: Cost differential based on different learning slopes

In recent decades, several non-linear experience curve models have been applied to several manufacturing and production settings (Moore, 2015). Contemporary models have attempted to incorporate the decay concept to measure the impact of non-constant learning on overall performance. Nonlinear models introduce the trend and the boundaries for actual experience cost curve. Surprisingly, few studies on technological change in the renewable energy sector have systematically investigated the impact of the experience curve functional form on the accuracy of renewable energy technologies cost models and estimated learning rates (McDonald & Schrattenholzer, 2001; Candelise et al., 2013; Elshurafa et al., 2018; Lafond et al., 2018; Eising et al., 2020).

The aforementioned uncertainties have caused doubts about the dynamics and quantitative estimates of costs using experience curves; despite the consensus on the importance of technological learning to achieve low-carbon energy system (Takahashi, 2013). To address this gap, this research tries to identify and model modifications to the conventional experience curve model, used in solar PV technology cost forecasting, such that the estimated learning rate is modelled as a decreasing learning rate function over time as opposed to the constant learning rate that is currently in use (Honious et al., 2016). The next section is a review of the problem statement and the research objectives in more detail.

1.2 Problem Statement and Research Objectives

Rapidly decarbonising the global energy system is critical for addressing climate change, but concerns about costs have been a barrier to implementation (Papineau, 2006; Zhou & Gu, 2019). To achieve a global transition to a low-carbon energy infrastructure, a series of investment choices in both the public and private sectors must be made (Lafond et al., 2018). Making the right choices depends on our beliefs about the future cost trajectory of each possible technology. Solar power technologies historically have had high upfront technological costs, which makes the experience curve an effective way of looking at cost reductions via technological learning. Yet, learning has to be global (IEA, 2000).

Learning is the product of experience, "it is the very activity of production which gives rise to problems for which favourable responses are selected over time" (Papineau, 2006). However, learning associated with repetition of essentially the same problem is subject to sharp diminishing returns. Since Carr's observation (1946), empirical evidence from various industries has supported the assumption that technological learning is not linear (Baloff, 1966; McDonald & Schrattenholzer, 2001; Schilling & Esmundo, 2009; Rypdal, 2018; Hogan et al., 2020).

A strong empirical evidence came from the *Air Force Institute of Technology* with tens of studies trying to identify the most accurate functional form of experience curves applied to Defence acquisition programmes (Badiru, 2012; Moore, 2015; Honious et al., 2016; Johnson, 2016; Boone, 2018). According to Wilson (2012), there are always physical limits that prevent the concept of constant learning and growth. Wilson (2012) divided the technology's life cycle into a start or a "formative" stage that is then followed by a rapid growth stage, and a scale where average unit cost sees its major reductions, and finally a "levelling off" or mature stage where the unit cost frontier is achieved as shown in Figure 1.8:

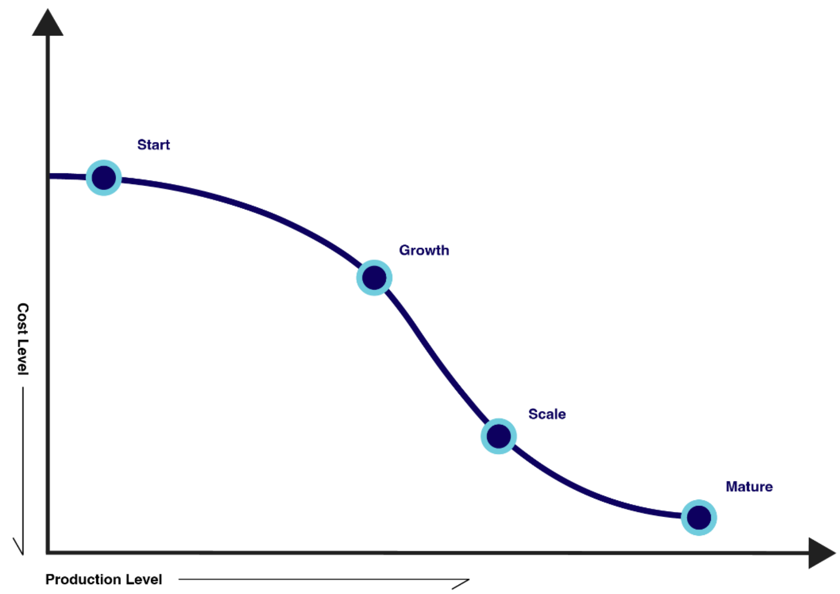

Figure 1.8: Technology life cycle stages

1.2.1 Knowledge Gap Identification

Wright's model has been the standard model in renewable technologies cost estimating procedures which assumes a constant learning rate. McDonald and Schrattenholzer (2001) analysed the variability and evaluated the usefulness of experience curves for applications in long-term energy models and provided the foundation for this research (McDonald & Schrattenholzer, 2001). However, where they focused on the variability of the actual long-term learning rates between energy technologies, this research directly evaluates the flattening effect near the end of production runs using non-linear experience functional forms.

Hansen et al. (2017) attempted to make a model selection between exponential and the non-linear Logistic growth of wind and solar power based on standard curve fitting to historical data (Rypdal, 2018). The Logistic growth curve is one of the sigmoidal curves that has an initial slow growth followed by an exponential growth phase that converges to a maximum value due to a nonlinear saturation mechanism. Hansen et al. (2017) concluded that the logistic curve generally yields “better fit” with a statistically significant decline in the relative growth rate (Hansen et al., 2017; Rypdal, 2018). Their findings are important, yet the assumption behind their study is built on growth curves analysis, not experience curves[2]. Historically, derived learning rates were sometimes combined with growth projections of a certain technology to derive future cost trajectories, yet these two curves are independent (Shukla et al., 2015). Experience curves are specifically used as a cost forecasting tool that estimates the learning rates using cumulative production data as the independent variable of the model.

Despite the interesting findings by Hansen et al. (2017), the main output was a direct comparison between learning rates with no error comparison mechanism between the models found. Another key study on growth in the solar PV industry was carried out by Rypdal (2018). Rypdal built on Hansen et al. (2017) findings and lead another statistical comparison between models used in solar PV growth curves context (Rypdal, 2018). Rypdal provided a better explanation on the methodology used to calculate and compare errors between the models.

That been said, studies that discussed non-linear forecast models on solar PV modules belong largely to the growth curves family (Hansen et al., 2017; Rypdal, 2018). Despite similarities, growth curves are different in context and assumptions from experience curve as a cost analysis tool. Therefore, the choice for energy technologies, and solar PV modules in specific, came as a result of the gap in this field. Experience curves remain underdeveloped tools for energy policy in spite of the rich literature on the phenomenon and the use of the curves as planning and management tools in technology-intensive industries (Badiru, 1998).

Using simple models as quantitative technology forecasting methods can be possibly explained by the fact that emerging technologies offer only short time series potential to begin with (Goswami et al., 2004;

[2] More details on growth curves can be found in Chapter Two.

Spatti & Liboni, 2016). This is typically further weakened due to governmental regulations and industries often seek to protect proprietary information. This resulted in using simple methods with limited theory and data. However, the situation has improved for solar PV technologies for example, with almost 30 years of deployment and progress, which makes today a perfect time to highlight the importance of evaluating contemporary models in renewable technologies cost forecasting (Elshurafa et al., 2018; Samadi, 2018; Dutta & Das, 2020; Eising et al., 2020).

The conventional experience curve model is not the only model that describes the relationship between cumulative unit numbers and production cost (Yelle, 1979). Other geometric forms of the experience curve model have been suggested in different industries since Wright's paper (1936). Some of the geometric models are: (1) the log-linear model, (2) the plateau model, (3) the Stanford-B model, (4) the DeJong model, and (5) the S-model (i.e. cubic L-C).

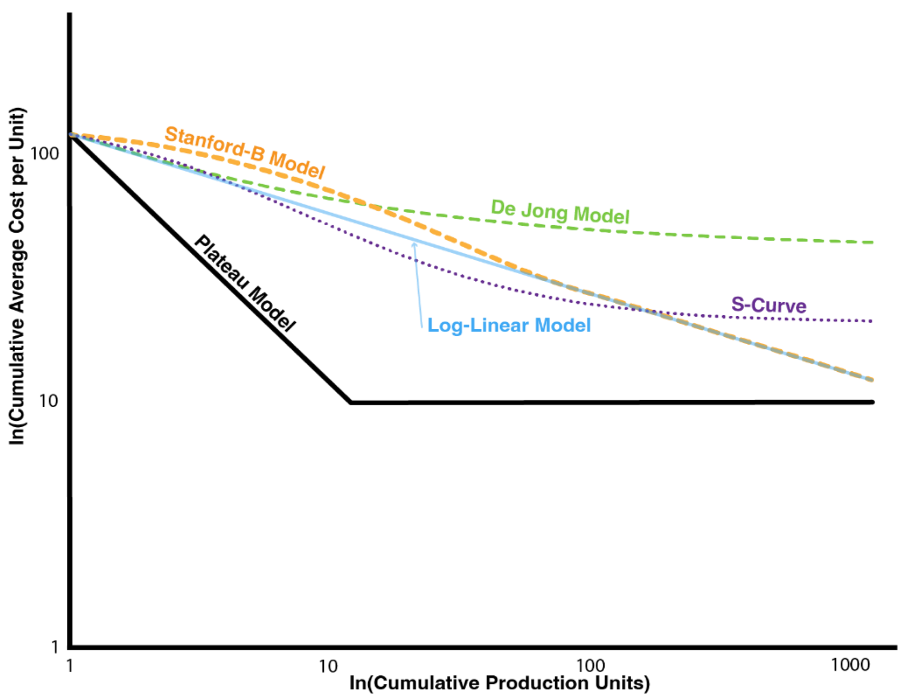

Figure 1.9: Several geometric forms of the experience curve model (Source: Yelle, 1979)

As for the solar PV industry, several mechanisms have been proposed to explain the technological learning and the observed relationships (Abell and Hammond, 1979; Arthur, 1988; Argote and Epple, 1990; Adler and Clark, 1991; Nemet, 2006), but generally they revolve around linear models. They neglected to reconstruct the shape of the curves or justify constant learning rates for solar PV technologies on the long-term (Wene, 2011).

The basis of this research is that more accurate cost estimates could possibly be made with alternative experience models that incorporate some aspects of plateauing and thus a declining learning rate. The most accurate function to be used for the slope estimate is what this thesis will attempt to discover (Boone, 2018). It aims to compare Gompertz and the Logistic models, two non-linear models that have the added precision of diminishing learning effects over time, with Wright's conventional model, and answer the question of whether solar PV modules cost estimates can be significantly improved upon with the application of alternative non-linear experience curve models (Moore, 2015; Boone, 2018). This implies reducing the forecasting error of the model and improve the dynamics that help understand future cost projection of a certain technology (Candelise, 2013). The gap this thesis aims to fill is summarised in a knowledge gap funnel below:

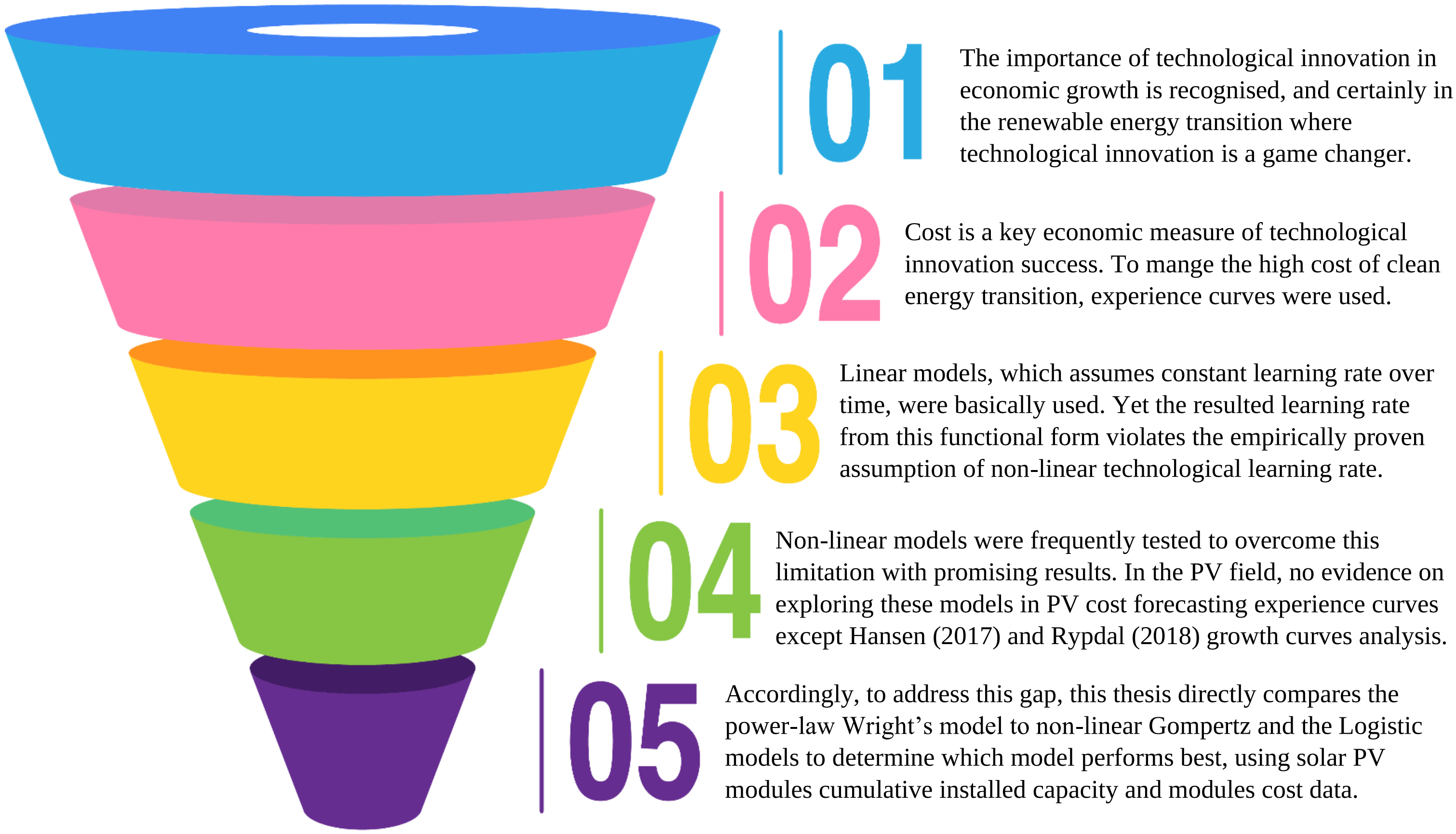

Figure 1.10: Knowledge Gap Funnel

1.2.2 Investigative Questions:

This research questions the constant learning rate concern by evaluating the experience curve performance in relation to the shape of the model applied to solar PV modules costs.

With this research focus, the following investigative questions are presented:

1. Can any of the contemporary experience curve models be applied to current solar PV modules cost estimating procedures? If so, which ones?
2. Are experience curve models that account for diminishing learning rates more accurate than the conventional experience curve model used toady? If so, which ones?
3. Which experience curve model is most accurate, with least forecasting error, at predicting the actual cost of solar PV modules?
4. Does Wright's experience curve truly reflect the production process and the dynamics of the solar industry compared to other experience curve models?

These results could turn out to be outstanding in an ongoing effort to increase estimate accuracy and improve the efficiency of solar PV technologies management. Therefore, the following chapters of this thesis will attempt to answer the above questions as well as outline the research findings that apply to each.

1.2.3 Implications

This thesis has two contributions. The first is to test the robustness of experience cost curves in solar photovoltaic (PV) energy to the alternative nonlinear models, which has been done in experience studies for other industries, but not for renewable energy technologies to our knowledge. Estimation is carried out on the assumption that cumulative capacity and/or industry production affect experience and thus the fall in price (Alchian, 1963). The second contribution is to highlight the importance of the economic-social-political (ESP) framework that serves as an embodiment of the critical experience curve dynamics for solar PV energy. This research deals directly with the economic aspect of this framework by investigating the reliability of one of the most used cost forecasting models.

If significant results are discovered as stated above, the final piece of analysis will be to determine which model serves as the best predictor of actual PV modules costs. A simple and common way to compare the models will be to compare which model has the least amount of the standard percent error. The smaller the percentage error, the more accurate the model. As things go, if there is evidence that one of the contemporary experience curve models (Gompertz or the Logistic model) is more accurate than the conventional model used today (Wright's model), then this result could potentially disclose a more accurate experience curve model in solar PV cost analysis, or at a minimum provide a proxy for further research.

1.3 Research Paradigm and Methodology

The premise of this research is to find the most suitable functional form that represents the econometric relationship between the production level and cost of the solar PV modules. To understand this reality, hypotheses were developed and tested using relevant statistical tests, which represents the epistemological approach of this thesis.

Research hypotheses are directly connected to the main research question and other complementary questions that are derived throughout the literature survey (Badiru, 2012). Developing these hypotheses is the first step in building the model that will help answer the research questions. Three hypotheses have been tested using available data sets that together shed light on the ability for experience curves to forecast future technology costs:

Hypothesis 1: One or more of the three experience curve models has a MAPE significantly different from the other models.

Hypothesis 2: One or more of the alternative experience curve models is significantly more accurate than Wight's model in predicting solar PV modules costs.

Hypothesis 3: The non-linear model, which accounts for both previous experience and the plateauing effect, has the lowest MAPE being the most accurate predictor of solar PV modules costs.

The epistemological approach of this research implies using the collected secondary data on solar PV modules, in statistical tests that will provide evidence to accept or reject the research hypotheses. In solar PV modules, the cumulative installed capacity (in MW) at the global[3] level is recommended, as well as the price (in $/W) of these modules in the global market (de La Tour et al., 2013).

That been said, the non-linear technological learning, observed in the cost-performance models, is the groundwork for the philosophy of this research. This belief is tested by a rigorous statistical comparison between the performance of linear and nonlinear models. Gompertz and the Logistic models appear like promising candidates with a long history of successful applications as growth curves and cost estimation tools (Buchanan et al., 1997; Akın et al., 2020). While it is true that the Logistic and Gompertz curves work well in theoretical models, their empirical use demands a widening of the spectrum of the sigmoid curves applied in renewable energy studies. Such a widening is the central objective of this paper, where the family of S-shaped curves in technology cost experience curves is first extended theoretically, before going to apply them empirically to solar PV modules cost models (Shukla et al., 2015; Hansen et al., 2017).

[3] There are reasons behind the choice of global data rather than regional data, which are explained in Chapter Four.

Once the data are collected and standardised for this research (e.g.: adjusted for inflation), the analysis should follow certain steps to answer the research questions. By using curve fitting techniques, each of the three models identified in section 1.1 of this chapter will be used to predict total silicon-based solar PV module costs. These curve fitting techniques (e.g.: Least Square Estimation) include minimising the sum of squared error (SSE) (Moore, 2015; Boone, 2018). The three models and their characteristics will be explained in depth in Chapter Four.

The predicted module costs will be compared to the actual module costs to calculate the error (also known as the residual), and then to Wright's model. The percent error from each one of the models will be compared to the rest using an Analysis of Variance (ANOVA), and Dunnett means test, which will each be explained fully in Chapter Five (Honious et al., 2016). A significance value (or Alpha, α) of 0.05 will be used to figure out whether at least one of the three models has a mean residual value that is different from the rest (Boone, 2018).

1.4 Research Philosophy and Approach

1.4.1 Research Philosophy

Beyond methodology as such, some practical issues are shared broadly across the science. However, in scientific research, the research philosophy acts as the core of the study and underpins the research design choices (Head, 2008). It serves as a framework that justifies how the research should be conducted based grounded on ideas about reality and the nature of knowledge (Collis and Hussey, 2014). It is therefore key to understand the philosophy adopted and the reason behind its choice, which plays an important role in the management of the research.

The two basic research philosophies are positivism and interpretivism. These two philosophies represent two fundamentally different approaches on how humans make sense of life and the world.

In positivism, reality is independent of us and can be observed objectively by researchers. On the other hand, in interpretivism, reality is seen as highly subjective because it is formed by one's perceptions. Interpretivism is concerned with exploring the complexities of social phenomena by achieving an empathic understanding of how the researchers view the world (Bryman and Bell, 2011; Saunders et al., 2012), using findings from a relatively small sample size (Collis and Hussey, 2014).

In consequence, this research study is underpinned by the positivist research philosophy. Positivism has originally emerged as a result of the perceived inadequacy of interpretivism to meet the needs in the natural sciences and scientific testing of hypotheses to find logical or mathematical proof that derives from statistical analysis on large sample sizes (Bryman and Bell, 2011; Saunders et al., 2012). This is the basis of the research design, which should aim to interpret findings in order to generate theories about the nature of the problem and possible solutions. Table 5.1 summarises the main features of both philosophies:

	Positivism	**Interpretivism**
Ontology: **What is reality?**	Naïve realism. Objective reality.	Subject and object are dependent. The real essence of the object cannot be known. Reality is constructed.
Epistemology: **How do you know?**	Dualism reaseacher-research. Replicable findings are "true". Reality can be explained.	Knowledge is interpreted. Reality can be understood.
Methodologies: **How do you find it out?**	Experimental, deductive. Mainly quantitative. Relationship cause-effect. Statistical analysis.	Interpretation. Mainly qualitative methods. Purposive and multipurpose sampling.

Table 1.1: Summary of the two basic approaches to research methods

1.4.2 Ethics and Credibility

The research was approved according to the University of Brighton Research Ethics Committee before the researcher contacted or involved any potential data collection. Moreover, some guiding principles were established when designing this research based on the principles for the ethical conduct of research as agreed by University of Brighton Research Ethics Committee (University of Brighton, 2018). The research is designed and undertaken to the highest standards of quality, integrity, and ethical propriety.

Reliability

In this context, the concept of reliability is defined as “the accuracy and precision of the measurement and absence of differences in the results if the research was repeated” (Collis and Hussey, 2014). Producing findings with high reliability can impose a challenge in positivist research due to the nature of the dataset and potential bias and/or misspecifications in quantitative research methods (Collis and Hussey, 2014).

Different researchers may collect different data and come to different conclusions at the end because of the size of data, the time period used, and the possible sensitivity of the model to certain internal and/or external factors (Denscombe, 2014).

To counteract potential negative impact on the reliability of the results, the researcher remained conscious of her own role in the research to eliminate or, at least, minimise potential bias in the findings. The researcher was also aware of the inherent human tendency to validate a man’s own beliefs, which is known as confirmation bias (Hallihan and Shu, 2013). Researchers may unconsciously emphasise views that fuel their pre-existing perspectives, while overlooking options that do not support these personal assumptions. In this study, the researcher tried to avoid confirmation bias and produce reliable results by consciously treating all data equally and avoiding any temptation to manipulate the analysis of the collected data (Denscombe, 2014). Furthermore, discussions and consultation with the research supervisors further contributed to avoiding researcher bias.

Validity

Validity is how the researcher assesses the quality of the chosen research design and methods. Should the research findings measure the phenomenon they claim to measure, the findings could be considered valid (Collis and Hussey, 2014).

On the appropriateness of the chosen methods of data collection and analysis, the data collected for the purpose of this study is pulled from sources that are known to be accurate and appropriate (Denscombe, 2014). The validity of the findings is further judged by the level of attention paid to ethical issues in the research design and the researcher's attempts to eliminate researcher bias over the research process.

Generalisability

Given the positivist research philosophy of this research, generalisation is possible in this study (Collis and Hussey, 2014). However, the findings are likely to be generalisable to settings similar to those that have been studied only (Honious et al., 2016; Boone, 2018).

Accordingly, the researcher tried to capture the features and complications of adopting experience curves as a strategic tool in technology cost forecasting and gained a comprehensive and deep understanding of this forecasting tool. The insights gained from the collected data on solar PV modules have enabled the generation of patterns and theories that ought to be true and applicable in other technologies that set out to become competitive ((Badiru, 1998; Denscombe, 2014; Moore, 2015; Johnson, 2016; Boone, 2018).

Code Availability

The code used in this analysis will be made available upon request.

1.5 Research Structure and Conclusion

In cost forecasting literature, there is a well-established fact that no single forecasting model is the "best" for all situations under all circumstances (C.-W. Chu & Zhang, 2003). The "best" is the robust and accurate for a long-time horizon that users of the model have confidence to use it repeatedly.

An interesting possibility is that there exists a non-linear experience curve, and a corresponding non-linear technological learning, due to differences in the rate of change in unit cost for a given technology over time (Muraleedharakurup et al., 2010). In this thesis, we advance the hypothesis that technical change, in general, can be ascribed to experience which is subject to diminishing returns (Carr, 1946; Baloff, 1966; Schilling & Esmundo, 2009; Hansen, 2017; Rypdal, 2018). The research performs an analysis of the experience curves of renewable energy sources, and in particular PV energy, which is the most visible example of cost reduction in this context.

Therefore, the primary goal of this thesis is to address the research question of whether the application of modern experience curve models that account for the flattening effect may provide more accurate cost prediction estimates than the conventional models often used in solar PV literature. The data analysis methodology will statistically compare the accuracy of two selected non-linear experience curve models against the conventional power-law model used in renewable energy studies. The identification of the most accurate model, supported by significant results, will become a turning point to future methodological changes withing renewable energy technologies cost studies. This thesis, however, does not go too far and says that the conventional experience curve models are wrong or statistically insignificant.

The next chapter will provide an introduction to the relatively new science of technological forecasting, which should help the reader put the research question in context. Chapter Three will provide a more in-depth look into the literature written on technology forecasting, economic growth and the experience curve theory, both in general and within the solar PV industry in specific.

Chapter Four covers in more details the characteristics and the attributes of experience curve models, the main types of these models, the limitation and econometric considerations, as well as suggested solutions to overcome some of them. This chapter will also provide in-depth descriptions of the three models presented. Chapter Five will open the discussion on the methodology used to investigate the research questions as well as provide more details on the collected data sets for the study. Chapter Six displays the data results gathered from the methods described in Chapter Five, and supported with relevant charts and graphs from the analysis. The thesis concludes with Chapter Seven, which contains a discussion on the conclusions of this research, the significance of the results and their potential impact, limitations of this study, as well as recommendations for additional research.

Chapter Two: Technology Forecasting in Perspective

2.1 Chapter Overview

As discussed in Chapter One, the emergence of new or improved technologies depends on successful completion of the innovation process. The innovation process occurs when a system of organised activities transforms an idea to a commercial technology successfully. Accordingly, technological forecasting methods provide context for innovation forecasting – one of the most important drivers of long-term economic growth (Wagner, 2014).

Technology forecasting is a widespread tool in the fields of engineering, economics, and public policy. Perhaps the most consequential applications are found at the intersection of these disciplines (Bailey et al., 2011). In the time of rapid technological change, powerful forecasting techniques are required to make adequate forecasts to take advantage of future opportunities (Jabery, 1975). Bright (1972) a pioneer in the technological forecasting field, highlighted the need for more integrated methods, and acknowledged the declining reliability of forecasts that are based on expert opinions (Bright, 1972). Such techniques do exist and using them is discussed within the technology forecasting discipline.

This chapter will provide a summary of the definition of technology forecasting and the major methods and applications in this field as of today. Technological forecasting typically varies by objectives, time horizons, approaches, and techniques (Bright, 1972). The chapter further summarises some of key methods in technological forecasting field, including qualitative methods (e.g.: intuitive forecasting, Delphi method) and quantitative methods (e.g.: trend extrapolation, experience curves, time series analysis) and the limitations of these methods (Griffin, 1985). The purpose of this chapter is to provide the reader with a background on this key term discussed throughout the research.

2.2 Technology Forecasting Definition

2.2.1 Definition of Technology

According to the *American Heritage Dictionary of the English Language*, **technology** is defined as "the entire body of methods and materials used to achieve [industrial or commercial] objectives." (Martino, 1972). It is any systemised practical knowledge, based on experimentation and/or scientific theory, which is embodied in productive skills, organisation, or machinery (Gendron, 1977).

Jabery (1975) defined technology as the "society's pool of knowledge regarding the industrial arts (Jabery, 1975). For the purposes of forecasting, Walk (2008) yet defined technology as "any human creation that provides a compelling advantage to sustain or improve that creation, such as materials, methods, or systems that displace, support, amplify, or enable human activity in meeting human needs".

In his book, *Technological Forecasting for Decision Making*, Martino (1972) added that technology means the tools, techniques, and procedures used to accomplish some desired human purposes. "It is the practical implementation of intelligence," said Ferre (Ferre, 1988). Martino (1972) also insisted not to restrict the definition of technology to hardware and scientific theories only. He explained that technology may include "know-how" and "software" and can be based on practical experience and not only on science. Jantsch (1975) agreed with Martino that technology compromises the entire notion of products with their total hardware and software contents. This broad definition was confirmed by Grubler et al. (1999) and Christensen (1992) who referred to technology as a process, methodology or technique that is embodied in a product design or in a manufacturing or service process to transform inputs of labour, capital, information, and energy into output of greater service to the industrial society (Christensen, 1992; Grübler et al., 1999). Luthans discussed another aspect and linked the concept of technology to its relationship with organisations as "mechanical techniques and abstract knowledge that are employed by people to help attain organisational objectives". Dubin (1969) summarised the general meaning of technology in two points:

1. Tools, instruments, machines, and technical formulas whose employment is necessary to its performance; and

2. The body of ideas which express the goals of the work, its functional importance, and the rationale for the methods employed (Dubin, 1969; Jabery, 1975).

2.2.2 Definition of Forecasting

On the other hand, the *American Heritage Dictionary* defines **Forecasting**: "To estimate or calculate in advance". The dictionary adds: "to make a conjecture concerning the future." (Martino, 1972) It is "a probabilistic statement, on a relatively high confidence level, about the future," said Jantsch (Jantsch, 1968). Jabery (1975) defined forecast as a reasonably definite statement about the future, yet it provides a base for present decisions. This depends, however, on unchanging or slowly changing environment (Jabery, 1975).

Forecasting, in general, aims to identify a desirable future as its final aim, and the ways to reach this aim as effectively as possible. According to Quinn (1968) managers must systematically analyse potential opportunities and threats in the environment to evaluate the present decision and maintain future growth. General forecasting, and especially technology forecasting could, therefore, modify the logical structure of decision-making models based on newly created variables (Quinn, 1968; Jabery, 1975).

2.2.3 Definition of Technology Forecasting

Given the wide range of applications it has, it is no surprise that **technology forecasting** has numerous definitions in literature. In his article, *Technology Forecasting Methodologies*, Kumar[4] defined technology forecasting as "the prediction with a stated level of confidence, of the anticipated occurrence

[4] The researcher was unable to identify the year in which this article was published by Binay Kumar/ Prof. (NM).

of a technological advancement within a given time frame". Kumar explained that this prediction should be supported by data and knowledge of experts in the field. Firat (2008) added that technology forecasting "applies to all purposeful and systematic attempts to anticipate and understand the potential direction, rate, characteristics, and effects of technological change, especially invention, innovation, adoption, and use" (Firat et.al, 2008). Bright (1972) added that technology forecasting may include a measure of probability, confidence or certainty (Bright, 1972). In his book, *Technology Forecasting and Management Action*, Jabery defined technology forecasting as a probabilistic assessment of future technology transfer based on a relatively high confidence level (Jabery, 1975). It is the ingredient of the planning process to define the probable future capabilities of science and technology (Jabery, 1975), and an effective tool in order to anticipate and understand the potential direction, rate, and effects of technological change (Porter and Roper, 1991).

In the study, *Persistent Forecasting of Disruptive Technologies*, published by The National Research Council (2010), technology forecasting is defined as "the prediction of the invention, timing, characteristics, dimensions, performance, or rate of diffusion of a machine, material, technique, or process serving some useful purpose." (The National Research Council, 2010) The committee at the National Research Council modified the original definition of Martino (1972) to reflect the evolving practice of technology forecasting over the years[5]. They added the rate of diffusion as a critical element as well as the material used.

Bright (1972) added a key condition to the definition of technology forecasting: the prediction has to be reproducible through a system of reasoning. This implies that results, using a logic to a given set of data, should be consistent regardless of the analyst. With this condition, Bright excluded predictions based on "rhetoric and intuition" from the definition (Bright, 1972).

[5] For more details, see Martino (1969)

2.2.4 Technology Forecasting and Technological Innovation Chain

Mansfield (1976) differentiates technological change to be the advance of technology that takes the form of producing existing products, or new methods of producing existing products, or the techniques of organisation and management. It is the process by which economies change over time in respect of the products and services they produce, and the process used to produce them (Mansfield, 1976).

Therefore, technological change can work to neutralise or disrupt depending on how management actions are perceived by the research workers and by the market. These alternations in physical processes have impact on the way work is performed and on the efficiency of the enterprise.

Cetron (1971), on the other hand, described technological change as the link between the past state-of-the-art and the technology's present and future states. Cetron (1971) believed that the understanding of technological change is key to develop appropriate plans. Doing this, institutes will be able to direct the technological change in a manner which will be beneficial to the organisation, and to the general advantage of all parties (Cteron, 1971).

Therefore, to understand the outcome of technological forecasting in a whole, a forecaster must further understand the various stages of technological innovation. The forecaster must clearly state the stage for which one is forecasting. Mixing of data and methods representing several innovative stages may lead to errors and confusion. With that said, Donald Schoen (1969)[6] identified the process of technological change as having three major stages:

1. Invention: the stage of creation a new product or process
2. Innovation: the introduction of that product or process into use
3. Diffusion: the spread of the product or process beyond its first use (Cetron, 1971).

[6] Schoen was not the first to define these stages as it is seen before in Schumpeterian growth model (see Chapter Three). However, Schoen formally introduced this process within the technology forecasting discipline.

As for technology forecasting science, Cetron (1971) pointed out that it is the diffusion of the technology that is more amenable to forecasting than other stages. The argument indicates that technological change can be assessed and forecasted, as well as its impact on society. This implies having a standard of comparison that allows to determine the worth or value of the technology under scrutiny, and to evaluate the technological change with acceptable standards of comparison (Jabery, 1975). With this in mind, technological change deserves additional attention. In their book, *Persistent Forecasting for Disruptive Technologies,* The National Research Council (2010) discussed the rationale of creating a new forecasting system to deal with the rapid changes government, corporations and institutions are faced with. “Small changes in one arena can trigger significant disruptions in others” with shrinking time frames to plan and react to disruptions (The National Research Council, 2010)

2.3 Technology Cost Forecasting in Perspective

Forecasting itself is not a new act as people have long forecast future lives, science, technology and other areas (Eto, 2003). According to James Bright (1972), a lead researcher in technology forecasting, academic awareness of the general concept of technology forecasting can be found as early as the 1880s in the USA (Bright & Little, 1979). There are many thousands of speculations, prophesies, essays and studies about technology and the future. “All have their place and serve a role – but not all are technology forecasts,” said Bright (1972).

However, the science of technology forecasting, as known today, is relatively new; dating back to the years immediately following World War II (The National Research Council, 2010). As mentioned earlier, technology forecasting (TF) attempts to predict the future characteristics of useful technological machines, procedures or techniques (Farmer & Lafond, 2015; Jabery, 1975). It is also concerned with the investigation of new trends, changes in environment that have also been attributed to technological causes as the dominant factor in social changes (Bright & Little, 1979).

However, and in the wake of the World War II, there were two realities that most manufacturers faced:

1. Technologies have become the key driver of the economic growth and technological learning is the main cause of improvements and, consequently, cost reductions in manufacturing firms (Jabery, 1975; The National Research Council, 2010).

2. Firms and organisations were expected to maximise the utility from their budgets in a fiscally constraints environment (Alchian, 1963). With increased financial scrutiny, great pressure was added on the accuracy of cost estimates to ensure the success of businesses (McDonald & Schrattenholzer, 2001).

Over the years, the purpose of technology forecasting in economic studies has been a source of confusion. In fact, like any other forecasts, their purpose is simply to help evaluate the probability and significance of various possible future developments so that managers can make better decisions.

Technological change and improvements in the instructions for mixing together raw materials lay at the heart of economic growth. A technological forecast deals with certain characteristics such as levels of technical performance (e.g., technical specifications including efficiency, speed, safety, etc.), and rate of technological advances (introduction of new techniques, new materials, costs, etc.). That been said, the success of the technology's expansion can be measured by the level of cost reduction, levels of technical performance and by the extent of market penetration of these technologies (Rao, 2008).

Cost is clearly one of the key factors that measures the development of a technology in a market. It is the key aspect of technological forecasting discussed in this study and represent the main scope of the research among other aspects of technology forecasting science. Jantsch (1968) went too far and explained that technological change is the weighted average of the change in factor prices (Jantsch, 1968).

Forecasting emerging technologies costs can help governments and enterprises in various countries to grasp the key to success in a new round of technological competition. The arrival of new technologies has multiple patterns and the development of emerging technologies costs with different emerging patterns will have fundamentally different requirements for governments and enterprises (Schilling & Esmundo, 2009).

Many policy decisions rely on predictions of how technology cost performance is likely to change as a function of time or of human efforts in research or manufacturing. Despite how inherently unpredictable the future cost is, it is worth trying to extract information from experts or from data to do better than a random guess (Rao, 2008).

These facts have raised awareness about technology cost methods and estimating tools which provide analytical construct to describe and project technology cost developments over the life cycle of a technology. They have quickly become very important as technological learning was considered the main cause of cost reduction. It is an essential discipline of the technology forecasting science that focuses on developing a range of probabilistic forecasting methods to generate estimates of future technology costs (Jantsch, 1968; Schilling & Esmundo, 2009; Wagner, 2014).

Technology cost level is the rate ot technological advances and serves as an indicator for the market share and commercialisation of a technology at a current life cycle stage (Wagner, 2014). According to Wagner, the development of commercial market shares usually mirrors the cost trajectory which, at the end, reflects the success of a technology. This starts with emerging technologies when they first try to enter the market commercialisation phase. The importance of understanding the cost level of a technology continues over the life cycle of a technology or a product to better understand the profitability at a certain point in time.

Cost reduction, however, is not constant and it cannot go forever (Papineau, 2006; Schilling & Esmundo, 2009; Johnstone, 2015). Also, market share growth slows down during maturity, following an S-shaped curve while cost development follows a reversed S-curve shape (Schilling & Esmundo, 2009).

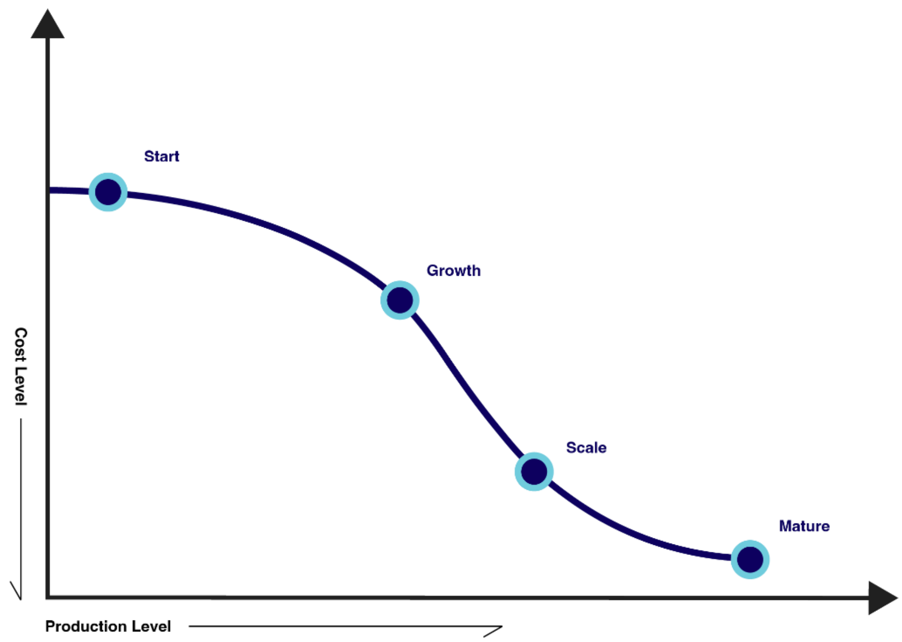

Figure 2.1 Technology cost reversed S-curve

Estimating technology cost is at the heart of this research. The focus is on this aspect of technology forecasting using the appropriate forecasting tools as explained later in this chapter. That includes analysing technological risk resulting in cost overruns as part of the technological cost analysis. Also, it is important to define the minimum fixed cost a technology cost reduction can achieve which is referred to as the floor cost (Alizadeh et al., 2020; Santhakumar et al., 2021). These risks are part of the technological cost analysis and cannot be neglected as explained in detail in Chapter Four.

2.4 Attributes of Technology Forecasting

The relatively youthful science of technological forecasting is incompetent *unless* it is related to action in present (Jantsch, 1968) Historically, the U.S. Navy was one of the major organisations which started formal technological forecasting to support the planning process and identify the likely opportunities and threats from technological setting for the future (Badiru, 2012). Technology forecasting has now assumed importance due to the structural reforms introduced in the economic system with a view to creating a market driven economy (Rao, 2008). It fosters the communication between various communities such as science and technology, industry and politics, and technology and general public and public administration (Jabery, 1975). In microeconomic terms, the opportunity cost of resources that is essentially stimulated by changes in technology is of prime interest to businesses. Essentially, technology forecasting is used for the purpose of anticipating and scanning emerging technological changes. It is also used in identifying suitable technologies by evaluating several alternatives (Jantsch, 1968; Neij, 1997; Badiru, 1998; The National Research Council, 2010). Among the most important attributes of technological forecasting is its role in *planning* and *managerial decision making*. These two attributes are discussed in more details below.

2.4.1 Technology Forecasting and Planning

Among a wide range of views, one view is shared which states that, in the long run, technology is the factor that most governs growth of the economy, and the cost and the availability of products (Grübler et al., 1999). Therefore, useful plans for the future must include a technological plan and estimates of cost reductions based on the technological learning. Jantsch (1968) described technological forecasting as one of several inputs to the planning process. It helps to perceive feasible technological options to prepare the decision-agenda on the technological level (Jantsch, 1968). Moreover, the principal task of technology forecasting is enhanced by the predominant role of technology in social change which is assumed to govern the dynamics of society for the planning period. The process includes evaluating the environment of technology plan, define the desired results and establish a quantifiable feedback system to measure technological progress. This process should help managers assess the life-cycle costs of technology and allocate resources and tasks properly.

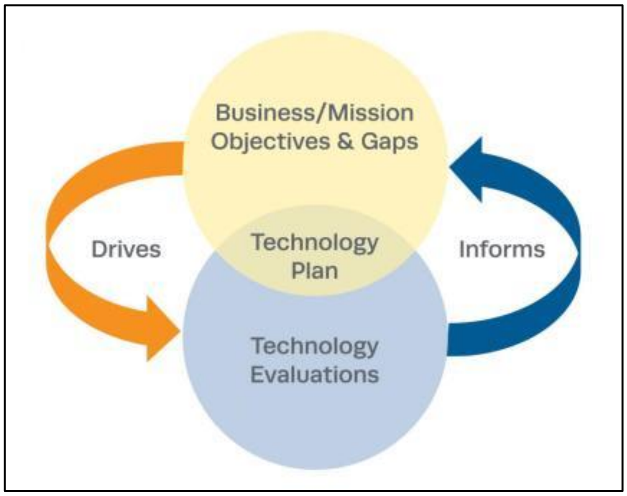

Figure 2.2: Technology plan and the life-cycle costs of a technology (Source: theintactone.com)

However, Jabery (1975) and others made a clear distinction between technological forecasting and planning (Jabery, 1975). Jabery quoted Schoen (1969) form *Harvard Business School* who explained that technological forecasting differs from technological planning. These two terms are often used interchangeably to refer to the same phenomenon. However, according to Schoen (1969), a forecaster attempts to predict what will happen technologically within the economy, while the planner's primary role is goal setting (Schoen, 1969).

From this distinction, technological forecasting seems to be a prerequisite for a successful technological investment planning (Jabery, 1975; Bright & Little, 1979; Farmer & Lafond, 2015; The National Research Council, 2010; Wagner, 2014).

That been said, the role technology forecasting plays in planning and strategic thinking for businesses is no more avoidable (Grübler et al., 1999). To make a useful economic forecast, it is critical to include the impact of technical change which is a vital dimension necessary for planning (The National Research Council, 2010). In today's rapidly-changing world, it is hard to find an alternative to technological solutions in many of the urgent problems – maybe until our knowledge of social engineering has matured to make non-technological solutions viable (Janstch, 1968).

2.4.2 Technology Forecasting and Managerial Decision Making

Anticipating technological change is an important managerial function. It helps managers to plan new products and avoid being technologically blind-sided by competitors with technologically superior products.

"The general function of any forecast is to provide a base for present decisions," said Jabery (Jabery, 1975). Technological forecasting is used to provide rational analysis to the decision-maker about the future technological environment (Janstch, 1968; Jabery, 1975; Grübler et al., 1999). It has taken its place as a management tool that is integrated with long-term planning and market and financial forecasting. It doesn't replace any of management's decision-making power; it mainly helps decision makers to assess future possibilities and consequences more adequately (Jabery, 1975).

Speaking of decision-making, technology forecasting also plays important role in identifying opportunity cost of resources. In microeconomic perspective, the opportunity cost of resources is directly affected by changes in technology. This is explained by the fact that technology forecasting provides early warning concerning potential consequences of new technology, with analysis of alternative measures for decision makers to choose from (Jabery, 1975; Boone, 2018).

2.5 Technology Forecasting Methods

The quality of forecasts greatly depends on proper selection and application of appropriate method (Bright, 1972). The most appropriate choice of forecasting method depends on what is being attempted to forecast, the rate of technological and market change, availability and accuracy of information, the planning horizon and the resources available for forecasting (The National research Council, 2010)

A fundamental distinction in technology forecasting studies, both quantitative and qualitative studies, is commonly drawn between exploratory and normative methods. Exploratory methods start at the present to see where the end goal might be, while normative methods begin in the future, asking what resources are needed to reach a certain goal.

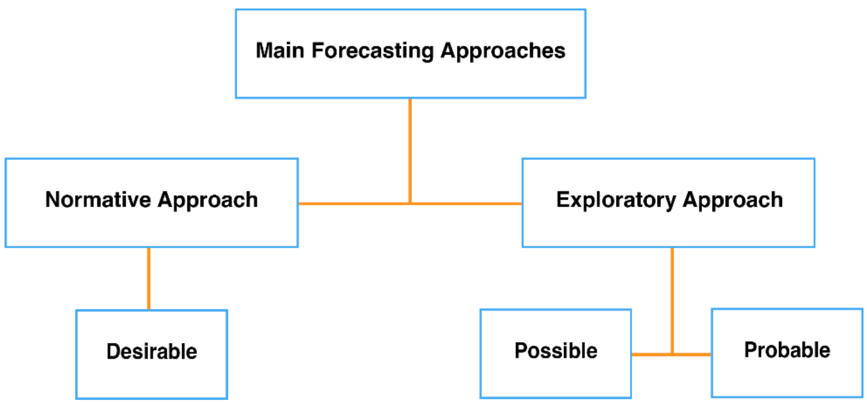

Figure 2.3: Exploratory versus Normative technology forecasting methods

2.5.1 Exploratory Technological Forecasting

Exploratory forecasting techniques start from today's knowledge and is oriented towards the future (Rao, 2008). In his book, Jantsch (1968) explains that exploratory technological forecasting begins with the past and present as their starting point and project the future in a heuristic manner looking at all available possibilities (Jabery, 1975). It typically simulates movement in the direction of technology transfer in systems which grow under s specific environment (Robert, 1969, Rao, 2008).

Exploratory forecasting includes a variety of methods for predicting the future state of a technology. Exploratory methods can be grouped into the following categories:

(a) Intuitive Methods:

Intuitive methods are based on the ability of one or more experts to assess the future (Rao, 2008). Examples on exploratory intuitive methods are:

- Individual forecasting prepared by experts in their field. This method is often biased, and probability of failure is high.
- Opinion polls where opinions are obtained from several individuals and combined (Jabery, 1975).
- Brainstorming in situations where evaluation of "unconventional alternatives" is needed.
- The Delphi method which is a group process technique for generally directing expert judgement towards a consensus though a several rounds of questionnaires for convergence of opinions (Rao, 2008). The Delphi technique has been, however, criticised over the years for being subjective, un-scalable and generally untested:

Figure 2.4: Delphi Forecast Method (Source: TRIO)

(b) Trend Extrapolation:

This method uses historical data rate to determine the rate of progress of technology in the past and extends it into the future (Roberts, 1969). Trend extrapolation implies that the factors which affected the past trends would continue its impact in the same known manner.

With extrapolation, the future value of a technical capability or production, from a technological activity, is an extension of its past performance (Bright, 1972; Persistent Forecasting of Disruptive Technologies, 2010; Boone, 2018; Santhakumar et al., 2021). Using known, available and in use technological events for which data is available, the forecasts are generally obtained using statistical time extrapolation technique and then extrapolating the trend in near future. The key concept of trend extrapolation methodology is that the past trend will generally continue to act in the same way unless there are obvious reasons to expect a change in the trend (Jantsch, 1968; Jabery, 1975). These reasons include the introduction of new efficient inventions or methods, or a change in the process of how the interacting forces in the market are behaving (The National Research Council, 2010; Kumar et al., 2021).

(c) Growth Curves:

Similar to the growth curves of biological systems, the evolution of technology as function of time has been found to follow same patterns. It is observed that similarities between biological growth and technological growth or technological parameters have been noticed over time (Kumar et al., 2021). Accordingly, the growth of technologies using biological growth models has been approved in literature for forecasting. A forecaster, however, must take into account the uniqueness of each field (The National Research Council, 2010).

Growth curves are one of the oldest techniques in technology forecasting techniques which are widely used in practical applications (Schilling & Esmundo, 2009). These curves usually show an “S-shaped” life cycle over years. There is enough evidence in literature that technologies tend to develop in patterns similar to the growth curves of biological phenomena (Badiru, 2012; Hansen, 2017; Rypdal, 2018).

Analysts use growth curves to extrapolate the future, for a set of data, based on present and past trends in a deterministic way. Among the most commonly used growth curves are the Logistic and Gompertz curves. They have a long history in predicting technological advances since their interception in the field of demography years before (Buchanan et al., 1997; Akın et al., 2020).

Growth curves have always been popular due to their simplicity over the long history of use in various fields. Non-linear growth curves presume that a technology will finally reach its upper limit at a certain time in the future. These curves are conducted to predict how and when this upper limit will be reached. Therefore, it is critical to estimate the upper limit which can be set by natural, fundamental, physical and chemical laws that rule the phenomenon being investigated (Jantsch, 1968; The National Research Council, 2010).

Growth curves are known to reflect how growth is slow initially until barriers are overcome, then the growth is more rapid until the limit is approached before the growth slows down again (Schilling & Esmundo, 2009). At this point, historical data gives correct coefficients of the chose equation which explains the distinguishable effort needed to find representative coefficients based on historical trends. Therefore, historical analogies and previous experience with a similar technology are key to forecasting technologies more accurately (Tjørve & Tjørve, 2017).

Like life cycles, experience curves are a type of growth curves that project the progress rate of one technology or the deployment of some technology into a market. Learning curve methodology has adopted other names along the way such as cost improvement curve, experience curve, or performance curve; however, the theory has remained relatively unchanged despite drastic changes in scale and technology (Alberth, 2006; The National Research Council, 2010; Takahashi, 2013).

Finally, curve fitting methods are known as a good tool to capture this complex behaviour of new systems to characterise technological change in reliable techniques embodied in experience/performance curves which is at the heart of this research. They have several advantages such as: the possibility of being automated and applied as a unifying conceptual framework to address all types of questions regarding technology forecasting. It also has a wider scope, focus and applicability (Sherman, 2020).

There is an increasing understanding in literature that experience curves have become an important tool for modelling and forecasting cost-quantity relationship, and they are treated as an idealised pattern describing this kind of technological progress in a regular fashion. Some analysts prefer to employ a particular form of the growth model for all technological growth patterns while others may prefer to employ mathematical transformations of these models.

(d) Analogy

In general, analogy is defined as a recognisable similarity or resemblance of form but with no logical connection or equivalence as usually found in a model. It is an attempt to predict possible futures by systematic comparison of a certain technology with a similar one in an industry by looking at historical data (Jabery, 1975). It is somehow a natural process that uses intuition based on similarities and is widely used in inductive inference. Thomas O'Connor review provides an insightful introduction and various applications of analogical techniques in various fields such as science, economics, and politics (Rao, 2008; The National Research Council, 2010).

As previously mentioned, growth curves presented a prevalent type of forecasting by analogy to predict the advance of technology. This is influenced by the observation that many technologies and products follow an S-shape growth pattern where there is a rapid growth stage that faces constraint as the curve reaches its upper limit (technology's saturation level) (Hansen et al., 2017).

Yet, Martino (1972) identified major drawbacks of analogies such as: lack of inherent necessity, historically conditioned awareness, and casual analogy. He however asserted that that these challenges can be lessened by a systematic approach that measures technological change with regard to several dimensions (technological, economic, social, managerial) to compare two analogous (Martino, 1972). Moreover, a key factor for a successful forecast by analogy is to choose the right technologies that are truly analogous to the one being forecast. That been said, attempts to forecast technological change mostly involved exploratory approaches, especially the Delphi technique, in the early decades of technology forecasting. However, most of the methods are only variants on simple trend extrapolation procedure which is known for (The National Research Council, 2010).

2.5.2 Normative Technological Forecasting

Normative technology forecasting first assesses future goals, needs, desires and missions, and works backwards to the present. In the normative forecast, objectives and goals are specified and, accordingly, the forecast works backward to the present to see the available capabilities that exist in the present to meet future goals (Rao, 2008). Depending on the situation, goals may force the choice of certain technologies over others. Janstch (1968) has stated that among reasons and attitudes that lead normative forecasting are: recognition of social responsibility toward the society, recognition of economic potential of some sort, hedging against threats or awareness of certain constraints imposed by natural resources, politics, etc. Taking these constraints into consideration makes normative forecasting meaningful and more reliable according to Jantsch (Jantsch, 1968). Famous normative forecasting techniques are:

(a) Relevance Tree

In 1957, C. W. Churchman et al. was first to address the concept of relevance trees linked with decision making in their introductory operation research book. Relevance trees are defined as an organised normative approach starting with a particular objective and used for forecasting as well as planning

(Jabery, 1975). It is an analytic technique that subdivides a broad topic into increasingly smaller subtopics thereby showing all possible paths to the objective and provides a forecast of associated costs and possibility for each element (Roberts, 1969). The basic structure looks like an organisational chart where information is presented in a hierarchical structure. The reason behind using the relevance tree is to evaluate systematically all the related technologies that would lead to the success of the intended objective (Jabery, 1975; The National Research Council, 2010).

The branches represent alternatives that are traced to several points from the forecasting perspective. The relevance tree provides a framework for identifying the deficiencies that need to be overcome. Relevance tress are usually relevant where, at a certain level of complexity, distinct can be identified and can be simplified at the same time by further breaking them down (Jabery, 1975). They are used to analyse situations with distinct levels of complexity, in which each successive lower level involves finer subdivisions. This could be used to identify problems and their solutions, establish feasibility, and deduce the performance requirements of specific policies and/or technologies (Roberts, 1969).

Relevance tree analysis has demonstrated to be a powerful intellectual stimulus to ensure that a given problem or issue is illustrated in comprehensive detail and that the important relationships among the items considered are shown in both current and potential situations. On the other hand, the development of relevance trees or morphological analysis, like most of Foresight methods, requires critical judgement thus the possibility of human error is present. Finally, if the underlying thought processes are not insightful, the outcomes of this method will be weak (Rao, 2008).

(b) Morphological Analysis

The term “Morphology” was first introduced by J.W von Goethe (1749-1832) in biology. The theoretical morphology concept was later eclipsed by Darwinian theory of evolution in the late 19^{th} century. However, Max Weber was the one who simplified, generalised and popularised simple concept-structuring methods applicable to virtually any area of investigation. Developed by Fritz Zwicky in 1942, morphological analysis is a normative technique that provides a framework for exploring all possible solutions to a particular problem. This involves the systematic study of the current and future scenarios of a particular problem (Jabery, 1975).

Morphology is identified as one of the most systematic available techniques for forecasting new products. The technique relies on a matrix that is usually called a morphological box (The National Research Council, 2010). In its simplest form, Morphological analysis allows for two key elements: a systematic analysis of the current and future structure of an industry area (or domain) as well as key gaps in that structure, and a strong stimulus for the invention of new alternatives that fill these gaps and meet any requirements imposed (Jabery, 1975).

2.5.3 Integration of Technology Forecasting Methods

As technological forecasting becomes firmly integrated into planning, the interaction between exploratory and normative technological forecasting finds an increasingly better-defined framework.

To conclude the discussion of the normative and exploratory technological forecasting approaches, it is important to realise that these two forecasting approaches are not competitive but are complementary (Jabery, 1975). For that reason, neither is "best," and if the question is asked, "which group of forecasting techniques should be used? The answer is "both".

To achieve the full potential of technology forecasting, knowledge and use of both exploratory and normative methods are essential (Jabery, 1975). This recommendation is seen in literature as early as in 1960s when Jantsch (1968) suggested to perform a complete technological forecasting exercise that includes an iterative process between exploratory and normative forecasting (Jantsch, 1968). Jabery (1975), also, emphasised how a correct forecast includes a correct interaction between the two elements of exploratory and normative forecast. He also explained how both methods are joined ultimately in a feedback cycle (Jabery, 1975). Bright (1972) refers to this way of thinking about technology forecasting tools as the integration between the normative and the exploratory methods.

Many experts in the field agree that it is advantageous to use several methods simultaneously, as each method can only deal with limited aspects of a forecasting case. “The full potential of technological forecasting is realised only where exploratory and normative components are joined in an iterative or, ultimately, in a feedback cycle,” said Jantsch (Jantsch, 1968).

Knowledge and use of both exploratory and normative methods are essential for effective technological forecasting. Following an iterative process between exploratory and normative forecasting, a complete technological forecast exercise is achieved. Cetron (1972) described the complementary relationship between exploratory and normative forecasting methods as follows:

"Visibility and discipline can be gained through the use of exploratory forecasting to define what may be possible. Vision and inspiration can be gained through the use of normative forecasting to define what is useful and desirable."(Cetron, 1972)

In his book, *Technological forecasting and management action*, Jabery (1975) quoted Cetron (1972) on the relationship between exploratory and normative forecasting: “exploratory forecasting becomes an input to normative forecasting,” said Cetron (Jabery, 1975). Cetron (1972) concluded that industrial application of technological forecasting requires that these two forecasting approaches are not competitive but are complementary. Therefore, no technological forecast method is the “best”, and both techniques should be used for the best results (Jabery, 1975).

2.6 Measuring Success in Technology Forecasting

It may appear that a good forecast is the one that comes true. However, Martino (1972) claimed that there are two things wrong with this criterion as follows.

Technological forecasts do not necessarily need to predict the precise form technology will take in a given application at some specific future date to be useful. In reality, technology forecasting is unlikely to be able to predict when, where, how, or why some completely new technology will develop (Bailey et al., 2011; Farmer & Lafond, 2016). It is even less likely to be able to predict who will make that breakthrough in the market (Bright, 1972; The National Research Council, 2010; Badiru, 2012).

That been said, it is important that the forecast quality is not evaluated by whether they came true but by its utility for making better decisions and not in whether it eventually comes true. The forecast is useful because it led to take an action that made things better. Thus, the value of the forecast is in its usefulness, not in its coming true.

These forecasts are intended to help decision-makers anticipate future events, avoid surprises, and allocate resources effectively. To that end, technology forecasts should be both as accurate as possible and properly qualified, so that decision-makers know how heavily to rely on them (Walk, 2008).

2.7 Limitations of Technology Forecasting

Establishing systematic technology innovation management which is capable of predicting technological change at the pace of innovation, is extremely important in a rapidly changing market. Although forecasters have had long complex algorithmic approaches at their disposal, their ability to effectively execute those approaches has been limited by many factors such as the availability of information and costs of information and analysis (Abernathy & Wayne, 1974).

The recognition that the development and application of a technology involves a large number of inter-connected activities makes it easy but unhelpful to describe this collection of activities as a "system". This point adds to the challenges that face technology forecasting (Bright, 1972; Boone, 2018).

Unavailability of data in an area of interest is a major challenge for forecasters. Data is not always stored in time-based data sets and commercial data services can be costly when available. However, as the new technology matures, the amount of data increase about this technology, which allows the use of more sophisticated data-demanding methods (Kochtcheeva, 2016).

Moreover, findings from different research emphasise the gap between theory and practice in technology forecasting. They suggest that usability is probably more critical than theoretical accuracy as technology management people seldom implement complex planning techniques and methods (Goddard, 1982; McDonald & Schrattenholzer, 2001; Thompson, 2012).

It is becoming apparent that some of the current exploratory forecasting techniques, with deterministic implications, will become either worthless or restricted in their application. This holds, in particular, for the currently most widely used technique, time-dependent trend extrapolation. Time-series will be used either only on the tactical planning level and for well-defined and complex sets of conditions, or- much more likely - they will be replaced by time-independent techniques, such as contextual mapping which has not yet been developed very far. Having said this, we emphasise Bright’s theory that technical-economic forecasting experiences is a very difficult, uncertain business. This field needs improved understanding of the process of technological innovation, and much better, practical tools for decision making on the technological future (Bright, 1972).

2.8 Conclusion

Anticipating technological change is an important management function (Bright, 1972). Predicting technological learning and change has been improving over the years. Several forecasting methods have been developed that project innovation and growth of technology in time. This chapter has introduced to the reader various practices and forecasting methodologies in the technological innovation context. These techniques play an important role serving as an input in the process of strategic planning and decision making. Perhaps the most difficult question in technological forecasting is to choose the most appropriate method in the correct timeframe (Bright, 1972).

Moreover, this chapter emphasied the importance of integrating (combining) technological forecasting methods to unlock the full potential of different forecasting methods. Using these techniques effectively, managers and policy makers would be able to close the gap between analytical and operational tools (Jabery, 1975). This is where technology forecasting fits including experience curves, the most used technique to quantify technological learning and, consequently, technological cost.

Chapter Three: Theoretical Literature Review

3.1 Chapter Overview

The purpose of this chapter is to summarise previous published research, as appropriate, to experience curve phenomenon, and examine how it applies to the energy transition today. It will also lay the discussion on how technology cost management has changed over the years and how this may or may not affect the way the clean energy technologies are predicted. As stated in Chapter One, many barriers still exist that prevent a more rapid diffusion of energy efficiency technologies including budget constraints and cost (IEA, 2000). Finding a more accurate experience curve model for predicting cost can make the decarbonisation process more efficient and control life cycle costs of technologies. Controlling cost, however, does not necessarily mean lowering the costs of the technologies; it means the energy analysts and managers will not have a better (or worse) picture of what energy technologies will actually cost (Johnson, 2016). Budgeting and cost management accuracy is achievable through accurate cost estimates.

Experience curves theory has been debated and modified for decades; however, the theory and its application to clean energy technologies management has remained relatively unchanged and has not adapted the current industrial theory or trend. While there is consensus on the importance of technology learning to achieve a low carbon energy system, the application of learning towards manufacturing and production is debated (Moore, 2015). Recently, several experience curve models have attempted to capture the flattening effect (aka plateauing, decay, or forgetting effect), in which a technology's performance begins to decrease over time. This concept of uneven and even degrading performance over time is the root of the flattening effect (or the forgetting theory), and the foundation of this research (Boone, 2018).

This chapter will deliver an in-depth review of present-day technological learning theories and modern "un-learning" curve methodology. The theoretical and empirical overviews will be followed by a description of the characteristics of these curves and economic considerations found in literature. It will also examine prior research on solar PV technologies in particular including methodologies and application used over the past four decades, and accordingly, the knowledge gaps this research is trying to fill (Elshurafa, 2018; Samadi, 2018).

3.2 Experience Curve Theory Review

3.2.1 The Smithian Growth Theory and Technological Change

Adam Smith (1776) and other classical economists provided many of the basic ingredients that appear in modern theories of economic growth. Ucak (2015) stated that Adam Smith (1776), David Ricardo (1817), Frank Ramsey (1928), and Frank Knight made important contribution to the economic growth theory that highlights the basic approaches of competitive behaviour, the role of diminishing returns, and the effects of technological progress (Ucak, 2015).

Smith's famous theory, that the division of labour (specialisation) improves the economic growth, was a profound one and he precisely linked it to technological progress. According to Smith (1776), economic growth is affected by factors such as population growth, capital growth, competitive-free traded market economy and the division of labour (technological progress).

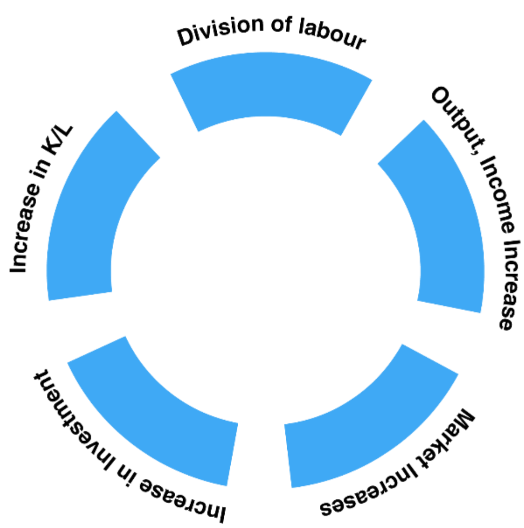

Figure 3.1: Adam Smith's virtuous cycle of growth

Joseph Schumpeter elaborated on this by explaining that the effects of technological progress are translated in the forms of increased specialization of labour and discoveries of new goods and methods of production. This idea is intrinsic in the endogenous growth models where knowledge and processes of creating knowledge are important parts of the production. In consequence, as firms and workers gain more experience on production, they can produce more efficiently, which is called learning-by-doing.

Despite the criticism, modern economic growth theories have still benefited from the Smith's thesis on economic growth. Technological change is widely recognised as the most important driver of long-term economic growth (Solow, 1956). Even if neoclassical economists[7] are not on the same wave with Smith, it is still relevant to review Smith's views on the determinant of economic growth to better understand the fundamental causes of it such as division of labour, human capital, learning by doing, increasing returns to scale and technological change.

Economists' research over the years led to the birth of the neoclassical model of economic growth. Among well-known growth theories linking economic performance and technological innovation include the Schumpeterian growth model (Schumpeter, 1934), Solow–Swan growth model (Solow, 1956; Swan, 1956), and endogenous growth theory (Romer, 1986, 1990). According to Schumpeter (1934), the process of technological change can be divided into three main phases: invention, innovation and diffusion.

[7] Arose in the early twentieth century, neoclassical economics is a comprehensive approach that uses supply and demand to understand and describe the production, pricing, consumption, and distribution of products and services in the market. It combines the classical economics' cost-of-production theory and the concepts of utility maximisation. Among leading names who contributed to the new neoclassical economics are Stanley Jevons, Maria Edgeworth, Leon Walras, Vilfredo Pareto, and others. In 1933, neoclassical economics adopted imperfect competition models. New tools were used in this era that helped to reduce the sophistication of its mathematical approaches, hence fostering the growth of neoclassical economics. Economists integrated Keynesian macroeconomic and neoclassical microeconomic ideas in the 1950s. The result of this synthesis was the neoclassical synthesis, which has dominated economic reasoning ever since (Solow, 1957; Eto, 2003; Ucak, 2015).

Schumpeter (1934) views this process of technological change as one of creative destruction, where technologies are subsequently replaced by newer ones (Schumpeter, 1934). In his model, Schumpeter emphasised the importance of innovations for social change, international competition, structural change and, most importantly, economic growth.

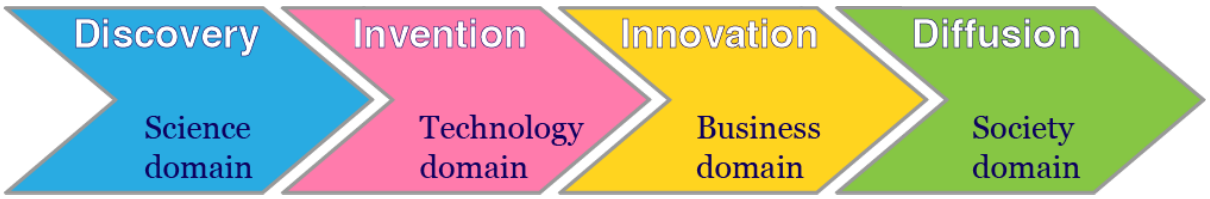

Figure 3.2: Schumpeterian growth model

In 1956, Solow and Swan (1956) constructed the neoclassical model of economic growth, where economists are primarily interested in the long run development of economies, where investment in physical capital and labour are identified as the key driver of growth (Moaniba, 2018). In their model, Solow and Swan (1956) seek to better understand what Adam Smith considered the fundamental causes of economic growth and the determinants of technological progress.

However, Arrow (1962) believed that the Solow-Swan model failed to endogenise technological changes in their model. Arrow argued that the reason of this was because Solow relaxed the assumption of constant relation between capital and labour and missed, according to Arrow, the empirically obvious point that the knowledge associated with technological change is continually growing as the result of production experience. Arrow (1962) generalised the learning concept and put forward the idea that technical learning was a result of experience gained through engaging in the activity itself in a process of "learning-by-doing" (Alberth, 2006). Accordingly, endogenous growth models were extended later by a more recent scholar, Romer, (1986), who provided a fresh theoretical extension and empirical perspective on the crucial effects of technological progress on economic growth (Moaniba, 2018).

The basic presumption of the Romer’s endogenous growth theory is that it “provides a theoretical framework for analysing persistent growth of output that is determined within the system governing the production process” (Moaniba, 2018). This implies that the knowledge and the processes of creating knowledge are essential parts of the production. It also emphasises that the more firms, workers and industries are experienced in production, the more efficiently they can use resources in advanced manners. Many subsequent studies by Muth (1986), Lucas (1988), McDonalds and Schrattenholzer (2001) and others, have identified different variables affecting endogenous technological change such as research and development, government policies, spillover effects and institutional factors (Goddard, 1982; Alberth, 2006; Papineau, 2006; Schilling & Esmundo, 2009; Dosi et al., 2017; Grafström & Poudineh, 2021).

There is evidence in literature that technological learning is the most important input in the process of innovation which drives the technological change (Arrow, 1962; Hollander, 1963; McDonald & Schrattenholzer, 2001; Alberth, 2006; Nagy et al., 2013). The importance of learning in certain innovative industries has been empirically documented and analysed (Ucak, 2015). Technological learning was mostly measured through improvements in production and cost due to experience and learning (Alchian, 1963; Goddard, 1982; Muth, 1986; Wright, 1936). However, Wene (2011) criticised the lack of a solid theoretical platform that explains the hypothesis of technological learning as a fundamental property of the learning system (Wene, 2011).

Different schools of thought describe the accumulation and the distribution of learning within the firm, in the economic sector and in innovation system, differently. The conception that learning-induced cost reduction as a product of *“experience”* was first introduced by Arrow in the 1960s. Arrow’s theory (1962) relates endogenous technological change to learning by doing and its economic implications. Accordingly, the term “learning curve” was frequently used to describe rather a narrow field that usually focused solely on labour costs.

On the other hand, Conway and Schultz (1959) discarded learning as an important contributor to manufacturing cost reduction. They argued that learning was persistent even when labour force had rapid turnover (Alberth, 2006; Nemet, 2006; Grafström & Poudineh, 2021).

That been said, the argument extended in this paper is based on the following premises: technological learning lies at the heart of economic growth, and it provides incentives for continued capital investments. Thus, technological change emerges mostly because of intentional actions taken by people who respond to market incentives. The last and the most fundamental assumption is that endogenous technological learning means that the costs are assumed to be a function of prior investments and adapts dynamically with different investment choices[8]. The technology cost forecast is yet an output of system optimisation.

At first, most studies of new products and technologies have been descriptive, attempting to identify consistent patterns in the sources of problem and solutions used, and characteristics of successful innovations (Roberts, 1969; Jabery, 1975; Turoff & Linstone, 2002). Later in literature, different methods for estimating the future costs of technologies existed and can be categorised as: (1) "bottom-up estimates", based on state-of-the-art research and engineering (Papineau, 2006; Neij, 2008; Thompson, 2012; Nagy et al., 2013), (2) "top-down estimates", based on extrapolating purely empirical trends (Alchian, 1963; Day & Montgomery, 1983; McDonald & Schrattenholzer, 2001; Schilling & Esmundo, 2009; Rypdal, 2018; Grafström & Poudineh, 2021), as well as (3) a combination of these two methods (Ferioli and Zwaan, 2009).

[8] On the other hand, exogenous learning means that technology cost is purely as a function of time, independent of any investment choices made during the energy system optimisation. That is to say, the technology cost forecast can be regarded as an input to the model (Kohler et al., 2006).

Benefits and drawbacks of the "bottom-up" estimates have been discussed over the years, yet they are out of the scope of this thesis. The following section provides a critical overview of the mathematical concept of technological cost "top-down" forecast models via experience curves as the scope of this study. In this context, technological change was measured and referred to as an improvement in cost due to experience and learning as explained below.

3.2.2 Experience Curve Definition

The roots of the experience curve observation can be traced back to early economic theories on the relationship between specialisation and growth, which were based, in part, on individuals developing expertise over time (Smith, 1776). The earliest paper that mentioned a concept like the experience curve was related to telegraph operators (Bryan and Harter, 1899). The original concept was first documented by W.L. Bryan and N. Harter in their study on telegraph operators, *"Studies on the Telegraphic Language: The Acquisition of a Hierarchy of Habits"* (Bryan and Harter, 1899). They published a research summary on how "time" is the measurement of the operator's performance. They measured the performance in words per minute (sending and receiving), and time was recorded in weeks from the experiment initiation. According to Bryan and Harter (1899), their findings show that performance increased rapidly early, but eventually diminished and performance stabilised as the experiment progressed[9] (Boone, 2015).

Early in literature, most learning analysis was done within the field of human psychology to better understand the influential factors for memorisation and information retention. Since then, learning analysis and studies have been applied to numerous disciplines of groups and organisational performance (Wright, 1936; Arrow, 1962; Alchian, 1963; Hollander, 1963; Abernathy & Wayne, 1975; Goddard, 1982; Day & Montgomery, 1983; Nemet, 2006, Badiru, 2012; Boone, 2018).

[9] This is considered the first observation on the flattening effect in the experience curves reported in literature.

Dr. Theodore Paul Wright (1936) is considered the first to formally bring learning analysis in a commercial enterprise. In his 1936 paper, *Factors Affecting the Cost of Airplanes*, and at the height of the pre-World War II build-up, Theodore Wright considered human learning among numerous factors that influenced aircraft production cost (Wright, 1936). He recognised the mathematical relationship that exists as a systematic decline in the number of labour hours required to produce an airplane when estimating and evaluating production process performance (Wright, 1936; McDonald & Schrattenholzer, 2001; Badiru, 2012; Moore, 2015; Boone, 2018; Grafström & Poudineh, 2021).

Wright theorised that as workers completed the same process, they eventually get better at it *at a constant rate* (Day & Montgomery, 1983; Neij, 2008; Samadi, 2018). From this aspect, Wright's observation clearly resonates with Adam Smith's economic growth theory and the division of labour explained in the previous section of this chapter. Wright's observation is also tied to the term "technological learning" which assumes an improvement in the technology performance as experience accumulates over time. The core idea is that when a new product (technology) is introduced to the market, the production cost per unit is initially high, but orderly decreases over time as cumulative production increases (Badiru, 1998; Papineau, 2006; Honious et al., 2016).

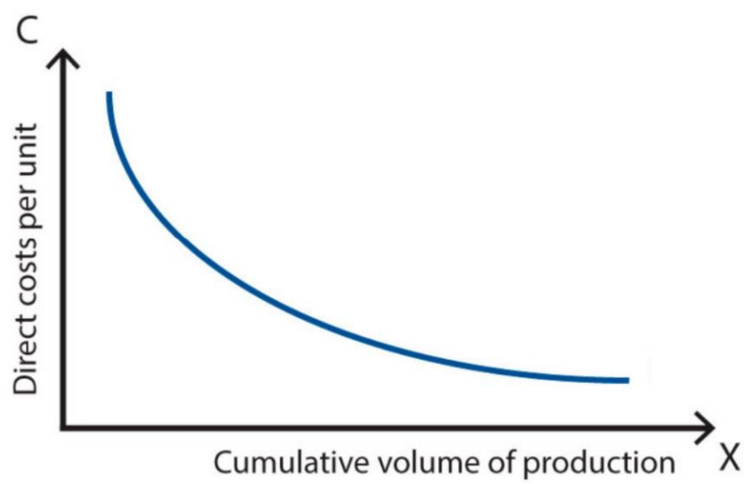

Figure 3.3: Simple graphical representation of Wright's observation

Wright's work remained relatively obscure until it was reviewed, a decade later, by economists at a think tank named RAND Corporation. RAND Corporation[10], was then founded by U.S Air Force, showed vital interest in the application of Wright's work to the production of war materials. The initial focus of RAND was to improve forecasting techniques, developed by RAND, that are based on expert opinion. RAND researchers, principally Olaf Helmer and Norman Dalkey, developed what is now known as the Delphi technique[11]; a systematic, interactive forecasting method which relies on a panel of experts. Nevertheless, the Delphi technique suffered from many drawbacks as it is still based on opinions. In consequence, several RAND's studies, which are more carefully prepared, lend credence to the experience phenomenon as follows. (Eto, 2003; Samadi, 2018; Grafström & Poudineh, 2021)

After the World War II, and through the RAND corporation, aircraft production data were utilised by Alchian (1963) in an attempt to compress the aircraft production experience of that era into a study based on Wright's phenomenon (Alchian, 1963; Hall & Howell, 1985). Alchian's paper was followed by Asher's classical study (1956) on post-World War II experience which summarises much of unpublished literature of that era. The RAND economists continued to be vitally interested in the application of Wright's work to the production of war materials—a phenomenon they eventually called "learning-by-doing" or the "learning curve".

When later applied to the total cost of a product (rather than to specifically labour cost), Wright's equation became referred to as the "experience curve" model. During the 1960s, the Boston Consulting Group (BCG) formalised the experience curve model as it is widely used today based on 24 selected industrial products (BCG, 1972; Henderson, 1984). The Boston Consulting Group (BCG) popularised the modern approach of

[10] A "think tank" created by the U.S. Air Force in 1946 to develop a complete "science of warfare" during the Cold War era.

[11] More details on the Delphi method can be found in Chapter Two

the experience curve based on the fall in "*cost*" that supposedly occurs over the total life of a product[12] (BCG 1968 in IEA 2000, Henderson 1973, Henderson 1984). The experience curve model, as developed by the BCG, has typically been applied to *the total costs* of a product, including the combined effect of learning, scale, and potentially other factors (Alchian, 1963). Conley (1970) supported the Boston Consulting Group (BCG) argument that the experience curve effect is not limited to manual direct-labour tasks, "but is quite general and seemingly applies to most of the activities undertaken within a company", said Conley (1970)[13].

Since then, this formulation (Equation 3.1) has been adopted in empirical studies to characterise learning phenomena in a wide range of industries, including studies on computer chips manufacturing (Alchian, 1963; Muth, 1986), shipbuilding (Rapping, 1965; Thompson, 2001), consumer products (Hollander, 1963; Yelle, 1979), energy supply technologies (McDonald & Schrattenholzer, 2001), fuel technology (Zeppini & van den Bergh, 2020), energy demand technologies and environmental control technologies (de La Tour et al., 2013; Hansen et al., 2017; Rypdal, 2018).

$$C_n = C_1 X^{-b} \tag{3.1}$$

where:

C_1 = direct cost of first unit of production

C_n = direct cost of nth unit of production

[12] It is reported that the full report of the (BCG) is difficult to obtain (Takahashi, 2013). Therefore, Patrick Conley's paper, the vice president of BCG at the time, and Bruce Henderson (1984) are usually quoted on this topic.

[13] In the following years, many researchers started to refer to the model as the experience curve model in their studies to reflect the association with technological change. As time has passed, many terminologies have been used more interchangeably to refer to the same phenomenon such as experience curves, learning curves, manufacturing progress function, performance curve, etc. Dutton (1984), however, urged not to blur important distinctions between these terms by using them interchangeably (Dutton & Thomas, 1984).

X = cumulative volume of production

b = experience rate (%)

Officially labelled as the experience curve by the Boston Consulting Group (1972), this phenomenon has had major impact upon corporate strategy, marketing strategy, and the management literature (Goddard, 1982; Henderson, 1984; Dutton & Thomas, 1984; Muth, 1986; McDonald & Schrattenholzer, 2001; Chu, 2003)[14]. Since then, experience curve models have been discussed in many studies and used in various areas of work measurement, job design, capacity planning, and cost estimation in many industries.

The Boston Consulting Group (BCG) files were later used in empirical studies to obtain cost data for different products in the chemical, paper, steel, electronic, knit product and mechanical goods industries. Wooley (1972) conducted one of these studies and concluded in results that strongly support the experience phenomenon with over 80 percent of the coefficient of determination (R^2) values above 0.80, and over 80 percent of the significance level at the 90 percent confidence level ($\alpha = 0.10$) (Wooley, 1972).

The popularity of the experience curve reached a peak in the 1970s. In 1979, Yelle (1979) summarised 90 articles on experience curves analysis. Dutton, Thomas, and Butler (1984) tracked down the history of progress functions by examining 300 articles (Dutton and Thomas, 1984). These studies supported Wright's original observation and provided evidence that costs, almost always, decline as cumulative production increases.

Despite this, the Organisation for Economic Cooperation and Development (OECD) cited the experience curves, as a technological forecasting construct, as the most neglected research area. "Since then, a new journal, *Technological Forecasting and Social Change*, has been born," said Yelle (Yelle, 1979). In the 1970s, Omega journal was born which as well has served as a useful vehicle for the dissemination of embryonic knowledge in this area (Yelle, 1979).

[14] For a time, it was also called the manufacturing progress function, before it has been tagged later the experience curve by the Boston Consulting Group (BCG).

In the 1980s, experience curves were less adopted in business management, strategy, and organisational research (Goddard, 1982; Argot and Epple, 1990). The experience curve concept was yet found in production processes studies such as studies by Dutton and Thomas (1984), Muth (1986), and Hatch and Kateregga (1987)[15].

Experience curves have later been utilised to study renewable energy technologies in 1999 by the International Energy Association (IEA) as explained in detail later in this chapter (Neij et al., 2003; Jamasb, 2007; Bhandari and Stadler, 2009; Lindman and Söderholm, 2012; Elshurafa et al., 2018; Yao et al., 2021).

Despite its popularity, Krawiec et. al (1980) disagreed with the logic behind the experience curve phenomenon and argued that the concept of experience is too ambiguous to be useful for cost estimation. Krawiec et. al believed that there is no logical reason to believe that costs will decline as a function of cumulative production (Krawiec et. al, 1980). In fact, Krawiec was not the only one who had the same point of view on the validity of experience curves. Lieberman (1987) said that as "firms were advised to use this model to gain a long-term cost advantage over rivals, unfortunately, many of these strategies failed and the concept lost its favour" (Lieberman, 1987; Papineau, 2006). Papineau also recalled the fact that this decline in cost is not, by all means, automatic; but depends on management's ability to force down costs.

Mathematically, an experience curve typically describes the relationship between a technology's specific costs (expressed in real terms) as the dependent variable and the technology's experience as the independent variable of the equation. In mathematical form, the relation is traditionally expressed as a power function (as seen in equation (3.1): $C_n = C_1X^{-b}$)

Taking the logarithm of both sides of Equation (3.1) gives a log-linear model as follows:

$$\mathrm{Log}\,(\mathrm{C}_n) = \mathrm{Log}\,(\mathrm{C}_1) + (b)^*\mathrm{Log}\,(X) \tag{3.2}$$

[15] For more studies and surveys see Wene (2000), McDonald and Schrattenholzer (2001), Junginger et al. (2005), Albrecht (2007), Hultman and Koomey (2007), and Neij (2008).

The experience parameter *b* in the Equation (3.2) indicates the steepness of the experience curve and can be estimated using regression analysis. Most studies use refers to *b* as the progress ratio, PR, or learning rate, LR, to characterise the steepness of the curve. The Progress Ratio (PR) is a widely used ratio of final to initial costs associated with a doubling of cumulative output. The learning rate (LR) is the relative reduction in price for each *doubling of cumulative production*.

The relation between E, LR and PR is given by the following equations:

$$PR = 2^{-b} \tag{3.3}$$

$$LR = 1 - PR \tag{3.4}$$

The cumulative production is depicted on the horizontal axis (X-axis) of a two-dimensional coordinate system, while the associated costs are depicted on the vertical axis (Y-axis). When plotted on a log-log scale, the relation between the cumulative output of the technology and its unit cost takes a linear form:

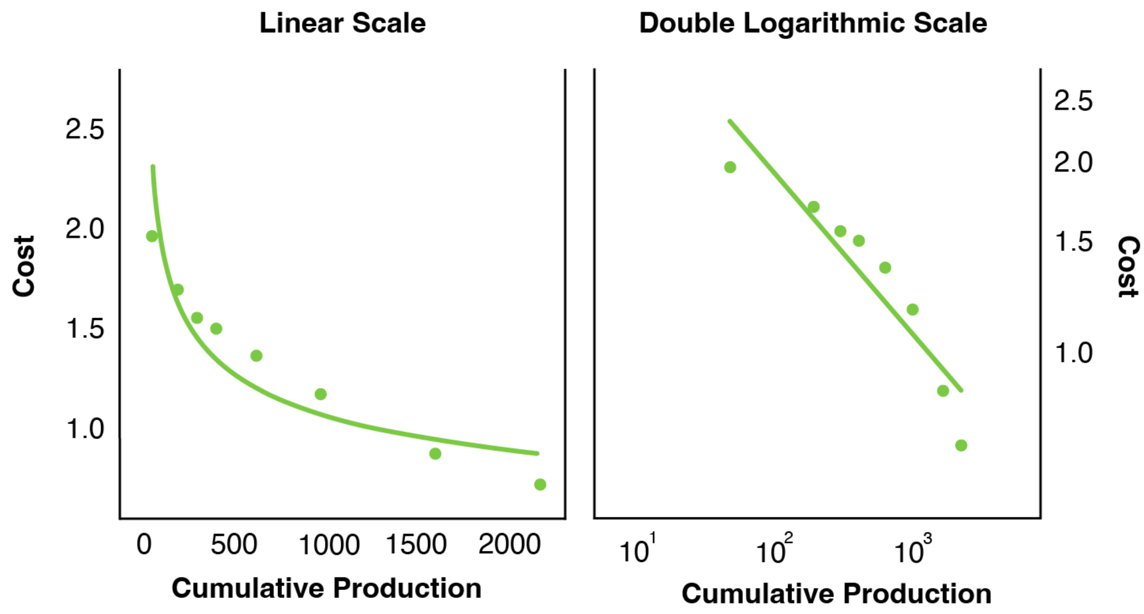

Figure 3.4 Graphical representation of linear scale versus double logarithmic scale

Over the years, experience curve studies explained the technological cost reductions graphically, but they, to a lesser extent, explained how the costs have been reduced (Neij, 1997). Similarly, no answer was found for the reasons of variations in the observed rates of the ‘learning’ parameter obtained. The parameters prediction dilemma has existed early in the literature on experience curves (Yelle, 1979). Estimation of parameters is particularly important as it allows decision makers to plan their activities more carefully.

Alchian (1963) was among the first to conduct a study searching for *factors* affecting the parameters of the experience curves. “Note how difficult it would be to separate the true learning parameter (b) from the tangle of coefficients,” said Alchian (Alchain, 1963). Baloff (1967) and Yelle (1979) also described the results of empirical approaches to estimating the experience curve parameters in separate studies (Yelle, 1979). The results were sufficiently interesting but could not be considered conclusive. According to Yelle (1979), the parameter prediction dilemma has never been solved, yet it still exists today with many studies published in the field (Yelle, 1979).

3.2.3 Learning Rate Dilemma

Using wartime airframe data, Alchian found that fitting experience curves with aggregate past performance of a single manufacturing in order to predict the future of a specific technology could result in a significant margin of error in parameter estimation. The importance of Alchian’s finding stem from the fact that, at that time, manufacturers had been operating on the assumption of constant 80% learning rate regardless of the differences between airframe types.

Few years earlier, Conway and Schultz (1959) concluded that the learning rate parameter varies substantially among industries, firms, products, and even types of work (Conway and Schultx, 1959). Conway and Schultz (1959) made it clear that “there is no such thing as the fundamental law of progress such as the "80% learning curve"[16] used in the aircraft industry. No particular slope is universal, and probably there is not even a common model. The contention that such exists is most difficult to defend either logically or empirically” (Conway and Schultz, 1959).

In the 1950s as well, Hirsch (1952) found that estimated parameters, and accordingly progress ratios, varied between products made by the same manufacturer in a study of seven different machines built by a single manufacturer. This fact, along with Alchian’s observation, provided an important basis from literature for our research question; as it is directly linked to the constant learning rate concern, and the potential consequences of this assumption on the reliability of the experience curves.

In the 1960s, Billon (1960) also searched for regularity in experience curve parameter estimation in order to improve forecasting. Billon (1960) emphasised Conway and Schultz’s (1959) conclusion that the experience curve slope varies among firms manufacturing similar product, among non-similar products manufactured by a single firm, and also among various models of a basic product type produced by a single firm (Billon, 1960).

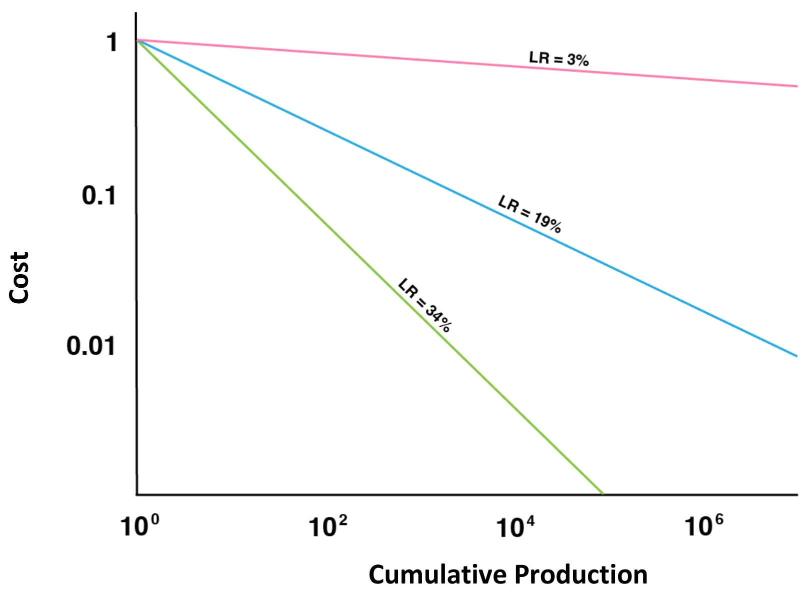

Figure 3.5: Variability in observed learning rate parameter

[16] The “80% learning curve” is identical to the learning index.

Cole[17], on the contrary, noted a “very little difference” in progress ratios between different types of manufacturing studies. Cole further concluded that “there is no causal relationship between the model’s slope and the first unit cost used in parameter estimation”.

More recently, McDonald and Schrattenholzer (2001) followed up on this argument with an important study where they analysed the learning rates variability and evaluated the usefulness of experience curves for applications in long-term energy models (McDonald & Schrattenholzer, 2001).

With this in mind, something has been observed, especially in the older literature on the experience curve phenomenon, that 'learning-by-doing', as measured by classic experience curves does not continue indefinitely (Carr, 1946; Elshurafa et al., 2018; Dutton & Thomas, 2021; Grafström & Poudineh, 2021). In reality, the early stages of the experience curve are rather flat, but later the curve on the log-log axes reverts to an *S-shape* instead of a *linear shape* (Carr, 1946; Crawford and Strauss, 1947, Baloff, 1966). In his paper, *Peacetime cost estimating requires new learning curves,* Carr (1946) noticed that cost improvement eventually stops, or more accurately, falls to a rate so slow that cannot be noticed in practice (Carr, 1946). The flattening effect at the end of the curve implies a non-constant learning rate estimated by a model rather than Wright’s original power-law model. Carr (1946) referred to Wright’s observation and stated that Wright was wrong assuming a linear learning curve model, and, consequently, a constant learning rate.

This conclusion was made by a large body of studies which supported Carr’s argument (Conway and Schultz, 1959; Baloff, 1966; Papineau, 2006; Badiru, 2012; Hansen, 2017; Rypdal, 2018; Grafström & Poudineh, 2021). “It is assumed that the learning rate is not linear, but rather smooth and dynamic where the learning rate is faster at the beginning and then flattens out,” said Köhler (Köhler, 2006). Even studies that reported constant learning rates, have referred to the flat tail at the end of the curve as seen in Wene (2015). The International Energy Agency (IEA) yet explained the decreasing learning rate in the experience curve as a “structural break” in the experience curve model (IEA, 2000).

[17] The researcher was unable to identify the publication year for Cole’s study.

Hall and Howell (1985) said that the graphical evidence on this was both direct and indirect. The direct evidence is that the linear falling region of the experience curve ceases, and is followed by a region that is practically horizontal (Carr, 1946; Crawford, 1947; Hall & Howell, 1985). Asher (1956) reported this phenomenon in the aircraft industry (Asher, 1956), while Baloff (1966) quoted this as "commonplace for the steel industry (Baloff, 1966). "

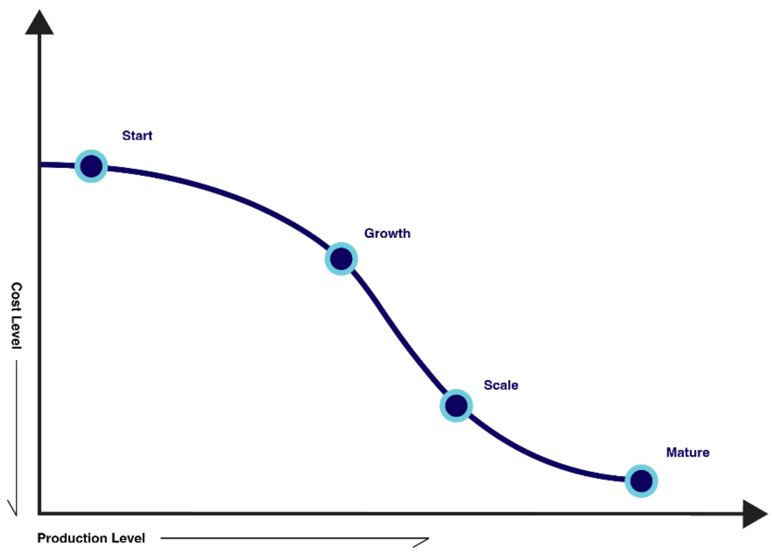

Figure 3.6: Non-linear experience curve phases

Hall and Howell (1985) stated that: "the fact that an almost horizontal region has not been encountered can never prove that one does not exist, but may simply mean that insufficient output has been achieved to approach it yet" (Hall & Howell, 1985). Jarne et al. (2005) talked about the same concept in a different way when they described linear models as "incomplete non-linear models" due to insufficient data at a certain point in time (Jarnet et al., 2005). The indirect evidence, according to Hall and Howell (1985) is observed when a set of experience curves are plotted as straight lines against time. These curves show a tendency to converge within the small region. Comparing the slopes of different linear curves provided indirect evidence on Carr's argument (Hall and Howell, 1985).

Carr's hypothesis genuinely highlights the importance of understanding the underlying conditions related to constant learning rates using a specific experience curve functional form (Rypdal, 2018). According to Carr (1946), following the linear assumption, regardless of cost-created practices and competition level in the market, can be dangerous and misleading (Carr, 1946). Carr concluded that, with all operations, experience curves can *rarely* be expressed by straight lines on log-log charts, and a "flat" is reached sooner or later on the curve (Baloff, 1966; Elshurafa et al., 2018; Grafström & Poudineh, 2021).

Reasons behind this observation stem from the fact that the linear model, used to estimate a constant learning rate, does not always provide the best fit in all situations. Since the learning effect does not continue indefinitely, and cost improvement eventually stops, experience curves do not continue indefinitely as well (Baloff, 1966). Typically, in the years of rapid growth of a technology, the learning and advancement occurs at a relatively faster rate, yet cost reduction comes about as fast in consequence. However, after a reasonable amount of time, achieving additional cost reductions becomes more difficult: a certain level of manufacturing 'maturity' is reached and doubling the production quantity requires more time (Carr, 1946; Jarne et al., 2005; Köhler, 2006; Grafström & Poudineh, 2021).

Grübler (2015) also argued that technology cost reduction happens quite fast in the early stage of the development process, but later phases stagnate and the potential for cost reduction declines drastically as the technology matures (Grübler, 2015; Elshurafa, 2018).

The experience curve (cost curve) can "intuitively" explain the slow-down phenomenon in the log-linear relation. Hence, the overall learning rate of a technology does not necessarily have to change "*in theory*". In a price-based experience curve, the market- and technology-structural change, and cost overruns, are found to alter the learning rate estimates. Besides the factors mentioned above, the changes in the data periods and *the choice of experience curve model specification* are also considered to impact the learning rate estimates significantly.

In the 1960s and 1970s, the observation made by Carr gained less popularity in application compared to Wright's phenomenon with hundreds of linear experience curves, and their inherited constant learning rates, have been plotted during this period (Yelle, 1979; Henderson, 1984; McDonald and Schentzler, 2001). Nevertheless, in the 1960s, Boeing Company found reasons to consider Carr's observation and to search for something other than Wright's log-linear model. Boeing, therefore, developed what is then named Stanford-B model that was used to incorporate design changes on the Boeing 707 (Baloff, 1966). Alchian (1963), Asher (1956), Baloff (1966), and Reis (1977) have reported similar results from various industries.

Detailed studies on the origin of experience curves models have been carried out by Carlson (1961), Yelle (1979), Krawiec and Flaim (1979), Badiru (1998), McDonald and Schentzler (2001) and others. Interested readers are referred to these studies for more details on the history of experience curves.

3.2.4 Definition of Experience and Learning Channels

Experience curve studies showed interest in finding specifications for the aggregate learning effect to select better proxies for experience (Alchian, 1963; Hollander, 1963; Goddard, 1982; Muth, 1986; Nemet, 2006; Nagy et al., 2013). *"Experience*" is typically treated as the independent variable of the experience curve model. Alchian (1963) was among the first who brought attention to the importance of factors used to form the experience curve and serve as surrogate for experience. Adler and Clark (1991) stated that cumulative output was originally privileged in the original model that Wright formulated in 1936, and by many later studies (Adler and Clark, 1991). Rubin et al. (2007) agreed with Adler and Clark that cumulative production or capacity behave as a surrogate for accumulated knowledge gained from various activities whose individual contribution cannot be readily discerned (Rubin et al., 2007).

Cumulative production can be identified as the technology's cumulative capacity built, cumulative number of plants, cumulative electricity generation, or else (Alchian, 1963; Papineau, 2006). Arrow (1962) and Sheshinski (1967) suggested cumulative investment as an alternative to cumulative output (Arrow, 1962;

Sheshinski, 1967). Time was also used as a complement to cumulative output by Cooper and Charns (1954), Moore (1965), Stobaugh and Townsend (1975), Nagy (2012). Day and Montgomery (1983) used market share as a surrogate for cost advantage based on the experience curve relationships. "Products which have a competitive advantage generate more capital than those that do not" (Day & Montgomery, 1983). Lastly, Alberth (2006) identified Research and Development (R&D) expenditure as a representation for the experience gained (Alberth, 2006). The bottom line is that choosing an appropriate definition of experience is case-sensitive and is again closely related to how the learning system boundary is defined for a specific technology (Samadi, 2018). The factors used to represent experience is discussed further in Chapter Four.

Since Wright's initial theory, there has been overwhelming literature trying to identify the reasons behind the learning process and cost reduction via the experience curve model. Initially, the learning process was investigated at individual company level (Asher, 1956). Interestingly, similar significant observations were made at industry level[18]. Both observations, however, indicate that the knowledge gained by an individual company through experience can ultimately be appropriated by other companies. Additionally, the literature suggests that experience gained over a certain technology's life in the market can lead to learning, acnd consequently cost reduction, through basic channels such as:

1. Learning-by-doing: as more units of a product (technology) are produced, workers and managers gain experience with the production process and may learn how to improve it (Badiru, 1998; Nemet, 2006; Papineau, 2006; Elshurafa et al., 2018; Grafström & Poudineh, 2021). Managers may act to improve the production process by increasing work specialisation or by reducing waste (Dutton & Thomas, 1984). Workers may also become more efficient in their respective tasks as they consistently repeat their individual production steps (Wright, 1936).

[18] For more details on these studies, readers are referred to Dutton and Thomas (1984) who studied the results of 108 experience curves in 22 industries (Dutton & Thomas, 1984).

2. Learning-by-researching: Research and Development (R&D) may play a larger role at early stages of development, while it may slow down in the more mature phases (de La Tour et al., 2013). R&D contributes to an expanded knowledge base, which in turn can stimulate further technological innovation, cost reductions and technology diffusion in the market (Yeh & Rubin, 2012).

3. Learning-by-interacting: through interacting with users about problems related to the use of a product or a technology, manufacturers learn from actual on-site experiences of the users. They, the manufacturers, can use this information to improve their respective products (Alberth, 2006). Even users may gain experience by using a technology and learn how to install and operate it more efficiently. Those formal user groups who interact with each other can strengthen this kind of learning via networking effects (Day & Montgomery, 1983). Accordingly, companies, users and other stakeholders – such as research institutes and policy makers – can learn from one another through formal and informal information exchange ways (Hollander, 1963; Day & Montgomery, 1983).

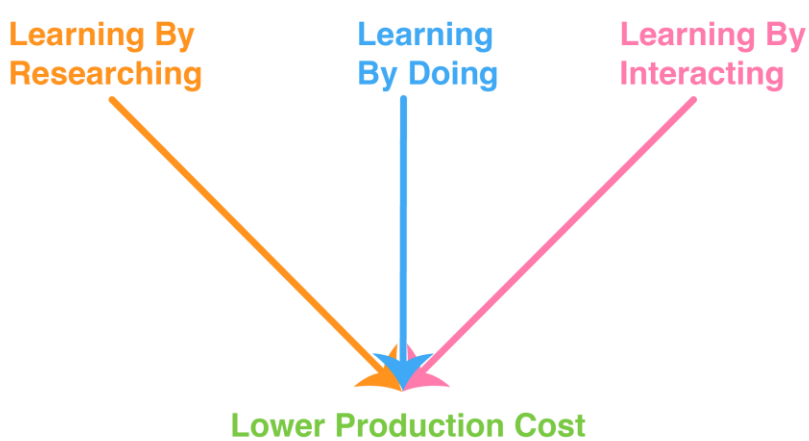

Figure 3.7: Experience curves basic learning channels

It is normally difficult to distinguish the contribution of combined effects of a large number of factors to the process of learning. Nordhaus (2014) quoted Alchain (1963) saying: "Note how difficult it would be to separate the true learning parameter (*b*) from the tangle of coefficients" (Nordhaus, 2014)**.** Various factors such as scale, learning and technology advancement, usually coincide and it becomes hard to measure the relative importance of their effects (Abdou & Mahmoud, 1977; Dutton & Thomas, 1984; Elshurafa et al., 2018; Samadi, 2018). Take economies of scale as an example as, frequently, the technological progress has been attributed to the gained scale (Silberston, 1972; Papineau, 2006; Farmer & Lafond, 2015; Healey & Grubler, 2015).

Hollander (1963), however, in a study on the sources of efficiency increases at DuPont rayon plants[19] concluded that "only ten to fifteen percent of the efficiency gains were due to scale effects whereas the remainder was accounted for by technology and learning" (Hollander, 1963). Similar results on economies of scale relevance as a cost reduction driver were found by Stobough and Townsend (1975) and Liebertnan (1981). Stobough and Townsend (1975) reported that static scale economies did not account for price changes to the same extent that the confounded experience variables of learning, technology and *dynamic scale* did (Stobough and Townsend, 1975). Liebertnan (1981) found a 71% experience curve when scale, new plant introductions, and new competitive entry were confounded with cumulative volume while the slope rose to 77% when these variables were separately analysed (Liebertnan, 1981).

Nevertheless, scale effects remain to be an important source of technological learning (Day & Montgomery, 1983; Grafström & Poudineh, 2021; Papineau, 2006). Plant-level scale economies result from capital cost savings (as the scale of a plant increases, the capital costs increase less fast), an increased potential for division of labour, and better utilisation of indivisible resources. Firm level scale economies derive from

[19] According to Yelle, Hollander's study, in 1963, was a significant departure from the classical topics in experience curve studies. Hollander addressed the relationship between factors such as technical change, capital investment and increased productivity due to experience and learning. "This significant study has not generated the attention it deserves," said Yelle (1979).

overhead economies (e.g., R&D and top management), economies in bulk handling (e.g., volume discounts), inventory economies, and marketing and financial economies (Hollander, 1963; Farmer & Lafond, 2015). Thus, while scale plays an obvious role, it does not, in these instances, appear to be a dominant component of the experience effect (Hollander, 1963).

Neij (2008) took this argument to another extent saying that experience cannot be gained irrespective of determined R&D policies and investment strategies by management to enhance development (Neij, 2008), neither the passage of time alone will lead to experience gain and cost reductions (McDonald & Schrattenholzer, 2001). Mishina supported this argument and stated that managements and organization's decisions, rather than gains in proficiency of the resources themselves, accounted for the overall success of the plant. Similar findings on the role of management were noted in a study of a truck assembly plant conducted by Dr. Dennis Epple (Argote & Epple, 1990). *Learning requires actions!*

Although the passage of time alone doesn't lead to experience gain and cost reductions, empirical experience curves are usually derived from time series of costs and capacities and thus carry invisible time labels with potentially interesting information (Nemet, 2006; Rypdal, 2018).

3.4 Limitations of the Experience Curve: Criticism of the Theoretical Concept

The popularity of the experience curve reached a peak in the mid-1970s, and firms were advised to expand output in order to deter entry and gain a long-term cost advantage over rivals (Papineau, 2006). Unfortunately, many of these strategies failed because firms did not consider the effect of learning-by-doing correctly, and the concept lost its favour (Lieberman, 1987; Papineau, 2006). Experience curves are known to be useful as a conceptual framework, however, using experience curves as a basis for policy determination imposes serious risks (Dosi et al., 2017; Elshurafa et al., 2018; Alizadeh et al., 2020). Alberth (2006) described the use of experience curves as "a temptation to overgeneralise without sufficient understanding of the underlying causes" of the cost reduction process (Alberth, 2006; Takahashi, 2013; Kavlak et al., 2018).

The limitations of experience curve analysis have been early reported by Abernathy & Wayne (1974), Goddard (1982), Day and Montgomery (1983), Dutton and Thomas (1984), IEA (2000), McDonald and Schrattenholzer (2001), Papineau (2006), Alberth (2006), Neij (2008), Nordhaus (2009), and others.

More recent literature on experience curves also acknowledged the limitations of this concept (Schilling & Esmundo, 2009; de la Tour, 2012; Badiru, 2012; Nordhaus, 2014; Boone, 2018; Rypdal, 2018, Hogan, 2020). Some authors are highly critical of the traditional experience curve concept in general, and of the application and interpretation of experience curve results in particular (Hollander, 1963; Krawiec, 1980; Goddard, 1982; de La Tour et al., 2013; Hansen, 2017).

A key criticism of the implications of the experience curve concept was made by Goddard (1982). Goddard criticised combining production data and cost in one single variable in what is called "high level of aggregation" (Goddard, 1982). As the concept does not attempt to explain exactly how experience leads to cost reductions, "it is a reflection of the forces and factors behind cost reduction not a measurement of it," said Goddard (Goddard, 1982).

Robert Solow (1957) also observed that, with any simplified model, there are aspects of economic life that are left behind (Solow, 1957; Goddard, 1982). The resulted model is so simple in Solow's sense that it cannot be mathematically manipulated to display anything more than it says. All else is speculation (Solow, 1957). As a result, "the learning curve hides more than it reveals," said Goddard (Goddard, 1982). For example, the significance of learning-by-doing compared to learning-by-using or learning-by-interacting cannot be revealed by simple experience curve analysis numbers (Day and Montgomery, 1983; Nordhaus, 2014).

Many academics point out that different factors were found to play significant roles in influencing technology cost developments, but these are not explicitly taken into account in experience curve analysis (de La Tour et al., 2013; Takahashi, 2013; Hogan et al., 2020). Examples on these factors in literature include: Learning through RD&D (Henderson, 1984; Kohler et al., 2006; Way et al., 2022), knowledge spillovers from other technologies, economies of scale (mass production) (Hollander, 1963; Nemet, 2006), cost changes of input materials and labour (Alberth, 2006; de la Tour, 2012), and changes in regulations (Boussaid et al., 2019; Eising et al., 2020).

With this in mind, Goddard concluded that "there is nothing wrong with the learning curve. But in combining annual production and time in the single variable, cumulative production, it hides more than it reveals." (Goddard, 1982)

Alberth (2006) argued that the theoretical construction of the simple one-factor experience curve model not only fail to appreciate these factors' respective roles in technology cost developments but can also lead to omitted variable bias (Alberth, 2006, de la Tour, 2012). Omitted variable bias happens when neglected additional independent variables are correlated not only with technology costs but also with experience. This often leads to overestimation of the relevance of experience in reducing technology costs and, the subsequent learning rates derived from these curves (Nordhaus, 2014).

Neij (2008) elaborated that experience usually has a strong correlation with time and other relevant variables such as knowledge gained through R&D, economies of scale or the suspected influence of inter-industry spill overs. Therefore, the high correlation between experience and technology costs, as seen in many experience curves studies, may actually be a misrepresentation caused by the correlation between experience and other key cost reduction driving factors omitted from the analysis (Neij, 2003).

The strong correlation between technology costs and experience is accepted by some critics, yet this does not necessarily mean that experience drives down costs according to them. Instead, Goddard (1982) and Lafond (2016) suggested that the causal relationship may mean that cost decreases (brought about by various factors other than experience) lead to more rapid technology deployment as the technology becomes economically more attractive (Lafond, 2016). The logic behind this matches the way classical economists viewed economic growth for a long time. Classical economists believe that economic growth depends on not only main inputs such as land, labour, capital, technology but also depends on social, economic and political structures (Abdou & Mahmoud, 1977; Henderson, 1984; Nemet, 2006; Papineau, 2006; Hogan et al., 2020).

To tackle this, de la Tour, for example, tested the potential presence of the omitted variable bias in solar PV technologies experience curve analysis. de la Tour et al. found that PV learning rates based on multi-factor experience curves (MFEC) are noticeably lower than PV learning rates based on models with experience only. They conclude that “the experience parameter is seriously biased when it is the only explanatory variable as it captures the influence of other drivers.” (de La Tour et al., 2013)

There is a need to address the criticism of the theoretical concept of the experience curve more extensively. Baloff (1966) stated that “the development of this potential will require some broadening of our conceptual understanding of what causes the learning phenomenon and, hence, where it is to be found.” (Baloff, 1966) This can be done by discussing the possible influences (and interdependencies) of factors other than experience on cost changes to derive plausible learning rates that take relevant cost-influencing factors other than experience into account.

Other suggestions are related to prepare in-depth case studies of individual technologies’ learning systems to analyse whether past learning may also have reduced non-plant level costs (such as external costs) or not (Henderson, 1984, Nemet, 2006).

Nemet (2006) points out that unlike the original company level experience curve concept, in which learning is assumed to stem from internal factors within individual plants, the industry level experience curve concept is based on the strong assumption that each company benefits from the collective experience of all companies (Nemet, 2006, 2009). In other words, the concept “assumes homogenous knowledge spillovers among firms." Nemet added that experience curve does not necessarily capture all types of improvements in electricity supply technologies. This is because such improvements do not necessarily manifest themselves in plant level cost reductions (Nemet, 2009).

Maybe one of the most useful suggestions came from Henderson (1984), who explained that all these cost reducing factors are valid but at different phases of the experience curve (Henderson, 1984). For example, at the beginning of a technology's life cycle, Research and Development (R&D) and learning-by-doing is more relevant, then this stops when economies of scale kick in, as shown in Figure 3.10. Unfortunately, Henderson (1984) didn't provide further details on how to test this idea empirically.

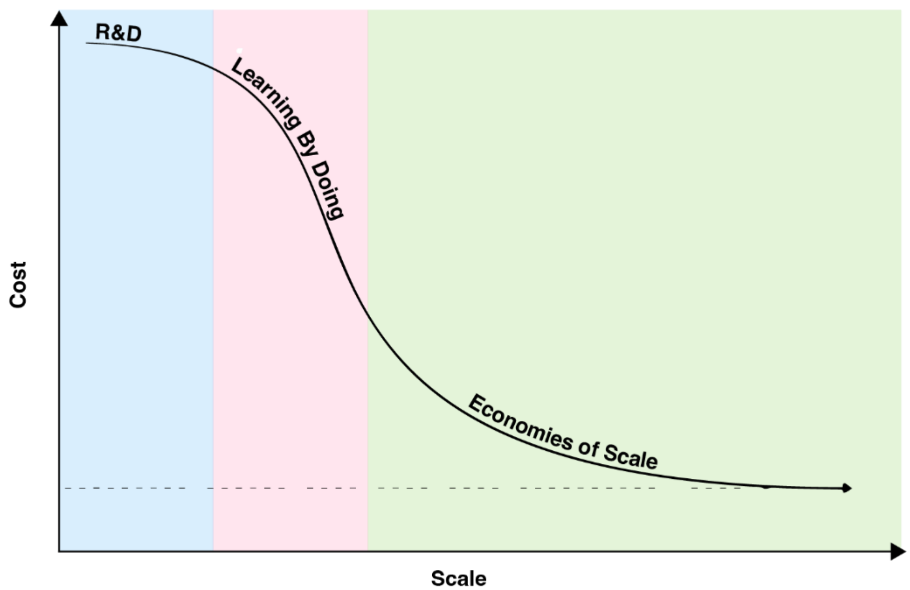

Figure 3.10: Henderson's cost reducing factors over the technology life cycle

Despite the critiques, experience curves have clearly gained business planners interest to help in strategic planning of production in different industrial sectors since the 1970s (Wright, 1936; Alchian, 1963; Preston and Keachie, 1964; Oi, 1967; Kopcso and Nemitz, 1983; Chen, 1983) until these days in production planning (Ebert, 1976; Muth, 1982; Badiru, 1998), cost estimation and control (Badiru, 1991), resource allocation (Liao, 1979), and product pricing (Washburn, 1972; Imhoff, 1978).

3.5 Literature Survey on Experience Curves Applied to Solar Photovoltaic Modules

Experience curve models have a long history in studies of manufacturing productivity (Muth, 1986; Badiru, 1992). Their perceived successes in technological forecasting have promoted them to be introduced in policy models of energy and global warming economics to make the process of technological change endogenous (Nordhaus, 2014).

In macro models, the treatment of technological change is still a major source of cost differences of climate change mitigation, despite various research efforts in the last years. Studies on technological change in the renewable power generation sector are also case studies on success or failure of specific eco-innovations such as windmills or solar panels. Most models compared in OECD and IEA studies set technological progress exogenously by assumption (IEA, 2000). Johnstone et al. (2015) examined the effects of public policies on innovation in the area of renewable energies in a cross-section of OECD countries over the period 1978-2003 (Johnstone, 2015). Johnstone found that the empirical results indicate a strong influence of policies on innovation in renewable energy technologies. The main finding is that endogenizing technical change using 'gains from specialisation' reveals dynamic growth patterns that cannot be reproduced in a model with exogenous technical change.

In the overview of the 1998 Energy Economics special issue on "The Optimal Timing of Climate Abatement", Carraro and Hourcade emphasised the notable influence that learning appeared to have on the calculation of declining costs of renewable energy technologies. They ran a survey, in the context of Energy-Economics-Environment (E3) models and concluded that learning introduced around a 50% drop in abatements costs.

In the International Energy Agency (IEA) publication of 2000, the IEA report presented a broad overview of the work covered up to the end of the 1990's and also presents the findings from the 1999 IEA workshop on this subject. Among recommendations was that experience effects should be "explicitly considered in exploring scenarios to reduce CO_2 emissions and calculating the cost of reaching emissions targets.

In regard the availability of data, there is uncertainty concerning the data prior 1990 on solar PV systems performance and costs (prices). For old data (before 2005), all studies on a global scale except IEA (2000) are based on two major data providers: Maycock, a historical expert of the PV industry, and Strategies Unlimited, a company specialised in semi-conductors selling market reports (Neij, 2008; Nagy et al., 2013). Since those datasets are the only ones available for old data, this creates a high uncertainty concerning the data prior to 1990. To our knowledge, it is not possible to identify the best data source among them.

Samadi (2018) provided a broad overview of the factors that typically influence the costs of energy technologies. He grouped these factors into four main clusters: learning and technological improvements, economies of scale, changes in input factor prices, and social and geographical factors. Within the literature on energy system models, learning and technological improvements and economies of scale are especially important as these can be directly affected by variables in the model.

The best approach on how to implement experience curves to energy technologies is debated in literature. In fact, there is no such a thing as “the best” approach; since models are unique and depend on individual technologies. When energy technologies consist of different parts that are assumed to exhibit distinct learning rates or different deployment curves, it seems more consistent to construct separate learning rates for these individual parts instead of a single learning rate for the entire technology. Speaking on solar PV technologies, it has been suggested that separate experience curves should be constructed for each component of the Balance Of Systems (BOS), instead of having an aggregated curve (Candelise et al., 2013; Elshurafa et al., 2018).

The PV learning rates listed in literature are either for all types of PV systems on the market (a market which has always been dominated by PV systems using silicon-based modules), or specifically for PV 3systems using silicon-based modules (de La Tour et al., 2013; Eising et al., 2020). Only a few studies have looked at learning rates for non-silicon PV technology, such as cadmium-telluride thin film modules, or for concentrating PV systems (Chu, 2009). Most of the identified learning rate studies for PV technology construct global one factor experience curves using specific module prices. The learning rates of these experience curves are typically between 15% and 25% (Candelise et al., 2013; Feldman, 2016; Grafström & Poudineh, 2021). No flattening in the PV cost behaviour was observed in the past until recently in growth curves studies (Rypdal, 2018), not experience curves. Most solar PV learning rate studies focus on module costs, however, there are indications that balance of system costs have decreased in the past to at least a similar extent to PV module costs.

In his paper, Harmon (2000) stated that "PV (manufacture is a high-technology industry, centered in the United States, Japan and Europe" (Harmon, 2000). Interestingly, in 2000, China was not even mentioned as one of the big players in solar PV manufacturing. However, China has become in just a few years a major player in the global PV industry. In 2021, China's share in all the manufacturing stages of solar panels (such as polysilicon, ingots, wafers, cells and modules) *exceeds 80%* (IEA, 2021). From the perspective of industrialised countries, this is disturbing. PV cells or modules manufacturers face tougher competitors and lose market share[20]. It also ruined plans of second movers such as France to create a local industry by stimulating the domestic market (de La Tour et al., 2013).

Equally, industrialised countries bore the cost of expensive incentive policies, the transfer of manufacturing capacity to China raises some concerns, as shown by the antidumping trade cases in the US in 2011 and in Europe in 2012 (Yang et al., 2018). On the other hand, industrialised countries benefit from these cost reductions, as demonstrated by the commercial success of Chinese panels especially in Europe. This provides cheaper PV electricity, helping to reach GHG emissions mitigation targets at a lower price, and participates in stimulating the manufacturing equipment and local installation business.

By surveying experience curves applied to solar PV modules in academic publications and reports from the International Energy Agency (IEA), and the International Renewable Energy Agency (IRENA), Single Factor Experience Curve (SFEC) studies made 85% of the studies on the topic. Only 15% of the studies included additional explanatory variables besides experience. More details on the characteristics of both

[20] Dozens of companies that filed for bankruptcy in the last years since 2011.

SFEC and MFEC can be found in Chapter Four. Table 3.1 summarises key studies on solar PV experience curves (Source: de la Tour, 2012):

Study	Geographical scale	Time frame	Learning Rate	Data Source
Maycock & Wakefield (1975)	Global	1965-1973	20.0%	n.a.
Tsuchiya (1992)	Japan	1979-1988	19.0%	n.a.
Williams é Terzian (1993)	Global	1976-1992	18.4%	Strategies Unlimited
Cody and Tiedje (1997)	US	1976-1988	22.0%	Maycock
Tsuchiya (1999)	Japan	1979-1998	17.6%	n.a.
IEA (2000)	Global	1976-1984	16.0%	EU-Atlas and Nitsch (1998)
		1987-1996	21.0%	
Harmon (2000)	Global	1968-1998	20.2%	Maycock
Wiliams (2002)	Global	1976-2000	20.0%	Strategies Unlimited
Parente et al. (2002)	Global	1981-2000	22.8%	Maycock
		1981-1990	20.2%	
		1991-2000	22.6%	
Poponi (2003)	Global	1976-2002	25.0%	Maycock
		1989-2002	19.5%	

Study	Geographical scale	Time frame	Learning Rate	Data Source
Schaffer (2004)	Global	1976-2001	20.0%	Strategies Unlimited
		1987-2001	23.0%	
	Germany	1992-2001	10.0%	Photex database
Papineau (2004)	Germany	1992-2000	15.0%	Extool Project, IEA
	Switzerland	1992-2000	10.0%	
	US	1992-2001	32.0%	
Nemet (2006)	Global	1978-2001	26.0%	Maycock
		1976-2001	17.0%	Strategies Unlimited
Van Sark (2006)	Global	1976-2001	20.6%	Strategies Unlimited
		1981-1990	16.6%	
		1991-2000	29.6%	
Swanson (2006)	Global	1979-2005	19.0%	Strategies Unlimited & other
Van Sark (2008)	Global	1976-2006	20.6%	Strategies Unlimited & other
Breyer et al. (2010)	Global	1976-2003	22.8%	Strategies Unlimited & other
		1976-2010	19.3%	

Table 3.1: Summary of key studies on single factors experience curves. Source: de la Tour, 2012

All experience curves results studies listed in Table 3.1 have the same specification of the dependent variable, module prices, and for the explanatory variable, experience. They, however, differ by the data source, geographical scope, and the time frame used (Boussaid et al., 2019). The module price is reduced by average 20% according to these studies every time cumulative experience doubles with 20% learning rate (de la Tour, 2013).

Besides experience, experience curve studies on solar PV module prices identified four other variables with potential significant effects on module cost. The first factor is Research and Development (R&D) through learning by searching. Kobos (2006), Alberth (2013) and de La Tour (2013) found that learning by searching has a positive effect.

Scale is another factor that was referred to multiple times in literature (Papineau, 2006; Rypdal, 2018; Samadi, 2018; Candelise et al., 2013). However, scale is not recognised in the early phase of the development of the PV industry where deployment is low. This is also inconsistent with the constant parameters' hypothesis discussed in this research. There is a variability in the scale parameter found in solar PV studies (Candelise et al., 2013).

The last variable discussed is the raw materials and input prices. The most important input prices discussed is the high-silicon, flat glass, and silver. Yu et al. (2011) found a strong positive correlation and effect of silicon price on module price. De la Tour (2012) emphasised this finding, while Wene (2015) took the argument a bit further to say that input prices are the true determinant of solar PV module cost (price) in the market. Wene said: "the fact is that after 2003, the prices for PV modules became very volatile, *increasing* until 2006/2007, stagnating and then falling strongly.

The irony is that most of this volatility is due to different national governments launching strong but uncoordinated deployment programs, which led to strong growth creating bottlenecks and scarcity costs, especially for PV-grade silicon ingots” (Wene, 2015). Figure 3.11 shows the jump in Polysilicon prices back then:

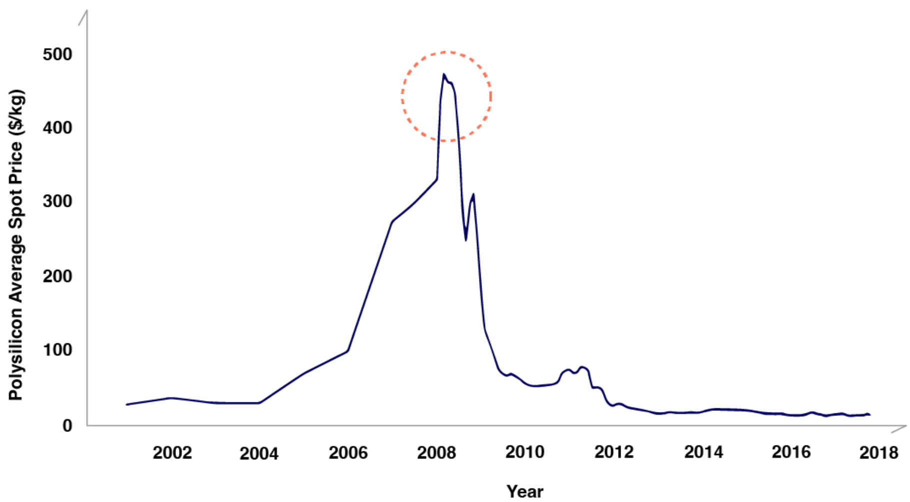

Figure 3.11: Polysilicon prices during silicon shortage time (Source: BloombergNEF)

The average learning rate found in Mutli Factor Experience Curve (MFEC) studies on solar PV modules was much lower than the learning rate from models with experience only as the explanatory variable, with average rate of 13.7% (Alberth, 2006; de La Tour et al., 2013).

3.6 Conclusion and Gap in Literature

To conclude this chapter, Figure 3.13 summarises the major milestones in the development of technological learning studies, including energy technologies studies in more recent times:

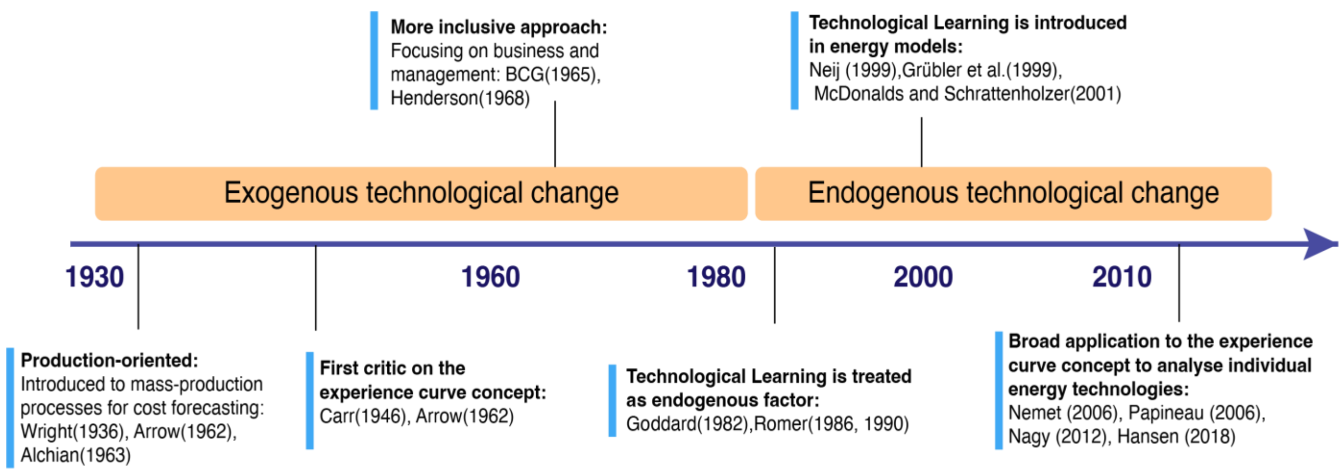

Figure 3.13 Key milestones in the development of technological learning studies

This chapter has reviewed the vast volume of literature on the theory and application of experience curves in general, and in solar PV energy technologies in particular. It has provided a systematic overview of the different ways in which such experience curves can be constructed and has discussed the learning rates issues from various empirical studies released between 1936 and 2021 for several technologies. The chapter has also provided a structured discussion of the limitations of the experience curve theory and its application, deriving suggestions on how to adequately address these limitations when constructing experience curves and making use of the associated learning rates. Finally, based on the extensive literature review, the research question sounds solid given the importance of having reliable learning rates estimates.

The next chapter, Chapter Four, will complement the Literature Review providing more details on empirical studies and efforts that tried to endogenize technological change in economic models of climate change mitigation using experience curve models.

Chapter Four: The experience curve and its application in the field of solar PV technologies

4.1 Chapter Overview

“The notion of experience as a driver of cost reduction is an attractive one,” said Papineau (Papineau, 2006). The experience curve phenomenon has been found to exist in several industries for the last 90 years as one of the technology forecasting tools. It has been adopted as a tool to help answer managerial questions on technology cost management given the simple quantitative relationship between different variables that represent a specific technology (Papineau, 2006; Nagy et al., 2013). The simplicity of the model has encouraged researchers to apply it to almost everything from airplane manufacturing to chemical processing, textiles production, and nuclear plants (Wright, 1936; Alchian, 1963; Baloff, 1966; Yelle, 1979; Neij, 1997; Bailey et al., 2011; Takahashi, 2013; Moore, 2015). Renewable energy was of no exception; as experience curves are found in hundreds of studies on low-carbon energy technologies.

Since the 1970s, when the popularity of the experience curve reached a peak, firms have been advised to use this model to gain a long-term cost advantage over rivals (BCG, 1972). Unfortunately, many of these strategies failed and the concept lost its favour (Lieberman, 1987; Papineau, 2006). In the climate change mitigation field, there is a newfound interest in experience curves as governments search for effective policies to meet the climate change goals (Rypdal, 2018; Alizadeh et al., 2020).

The purpose of this chapter is to complement the historical overview provided in the literature review, Chapter Three. It mainly discusses key econometric issues related to the construction of the experience curves, along with more details on the proposed non-linear models that are part of this statistical comparison. In the second half, this chapter provides more details on the solar PV technologies that were subject to technological cost reductions and how this industry is benefiting from technological learning.

4.2 Technological Learning and the Experience Curve

Technology learning is the leading phenomenon that dictates the future cost of a technology (Wene, 2015). As market actors accumulate experience, cost, and technical performance of a certain technology both improve. This incorporates a collaborative effort from various market actors from technology producers to technology operators and users (Papineau, 2006). The process is referred to as technological learning. Technological learning is often economic in nature and thus results in cost reductions (Day and Montgomery, 1983). Assessment of future costs is exceptionally important for emerging technologies that are new to the market. It appears as a collective label for features, events, and processes converging during the observed time to produce the experience curve (Wene, 2005). Therefore, changes in performance, productivity and/or cost (or price) of a technology in relation to the accumulation of experience are usually used as a proxy for technological learning-by-doing (IEA, 2000). Whenever a unit of a particular technology (e.g. Solar PV modules) is produced, some experience and learning accumulates which leads to a reduction in the production cost of the next unit of that technology (Bailey et al., 2011; Farmer & Lafond, 2015).

Experience curves are one of the most prominent methods to analyse technological learning (Louwen and Junginger, 2021). They mainly quantify and measure the results of the technological learning process (BCG, 1968; Abell and Hammond, 1979). This means that they could also be the artifact of simultaneous processes such as growth and innovation diffusion. In contrast to direct cost-estimate techniques, experience curves have the potential to describe cost reductions (or more broadly progress) for a technology over a range spanning a volume growth of orders of magnitude (Wene, 2015).

As explained earlier, the experience curve describes an empirical relationship between cumulative production of a technology and its unit costs. First observed by Wright (1936), experience curves analysis was measured by the *uniform* increase in labour’s efficiency only (Badiru, 1998) as a representation for learning. It referred to *constant* changes in the number of direct labour hours required to produce an airframe for each doubling of the cumulative production in a labour-intensive economy (Goddard, 1982).

In his paper, *Debunking the learning curve*, Goddard (1982) described Wright's observation that "the trend in unit cost assumed a surprising constancy in slope if the logarithm of unit cost was plotted against the logarithm of cumulative production. He called this the learning curve[21]." (Goddard, 1982) Day and Montgomery (1983) also quoted Yelle's definition who described the experience curve phenomenon as the [constant] systematic decline in the number of labour hours required to produce an airplane (Yelle, 1979).

In the mid-1960s, the Boston Consulting Group (BCG) generalised the notion of experience curves to apply to all costs such as marketing, distribution, administrative, etc. (Day & Montgomery, 1983). By now, the experience curves postulate that all value-added costs (and prices) will decline systematically in real terms as volume increases (BCG, 1968). Irwin and Klenow supported this approach by the BCG and defined the experience curve phenomenon as "the decline in production costs resulting from greater experience with the production process." (Irwin and Klenow, 1994).

This decline in cost is not, however, automatic but depends on managements' ability to force down costs. It is the result of an array of different cost-reducing processes (Kahouli-Brahmi, 2008) including various learning channels such as learning by doing (Arrow, 1962), learning by researching (Cohen and Levinthal, 1989), learning by using (Rosenberg, 1982), learning by scaling (Sahal, 1985) and knowledge spillovers) (Sagar and van der Zwaan, 2006).

The effect of these underlying factors, however, cannot be easily disentangled, which could lead to potential masking for the diverse drivers of technology costs as discussed in detail throughout this chapter.

[21] Goddard's claimed that Wright named his observation as the "learning curve". However, there is no evidence that Wright gave his observation a specific name.

Experience curves have been developed for many products and technologies in several industrial fields such as manufacturing, consumer products, energy technologies, and environmental control technologies. These studies share the empirical evidence for the existence of *constant learning rate* over time (Wright, 1936; Goddard, 1982; Henderson, 1984; Neij, 1997; Badiru, 1998; Alberth, 2006; Papineau, 2006; Bailey, 2011). Parallelly, they tried to propose a more theoretical clarification of how and why the technological learning occurs. Some of these studies are more established and accepted than others. These analyses, however, remain far from a generally agreed explanation of the observed robust cost–production relation (Ferioli, 2009).

Calculating the learning rate[22], via the experience curve phenomenon, is the main interest for cost analysts to project future cost developments. However, implementation of learning rates in a modelling environment, to endogenously capture likely future technological learning dynamics, raises several questions on the reliability of these technology cost forecasting models (Ferioli, 2009; Wene, 2015; Hogan, 2020). While the graphical evidence is impressive, it lacks a more theoretical and empirical justification on the constant learning rate in general of experience curves in general. Therefore, even if experience curves have proved useful for a number of purposes, they need to be handled carefully in order to deliver reliable and robust lessons for decision makers.

[22] See section 4.3 for more information learning rate calculation.

4.3. Construction of the Experience Curve

The experience curve is a well-known analytical concept that describes the cost reduction potential of a technology as a function of experience quantified in terms of cumulative production (Karali et al., 2015). In cost terms, the classical form of the experience curve is:

$$C_{t,y} = C_1 Q_{t,y}^{-b} \tag{4.1}$$

Where:

C = Costs of unit production ($/W)

Q = Cumulative Production (MW)

b = Learning parameter (i.e, experience index)

C_1 = Cost of first unit (depending on initial conditions)

t = Technology

y = Period (year)

The power law behaviour enables plotting of experience curves as a straight line on a double-logarithmic scale (IEA, 2000). This model is linear in the logarithm and may be estimated using regression analysis when data are available:

$$\log \mathrm{C}_{t,y} = \log\mathrm{C}_1 - b * \log\mathrm{Q}_{t,y} \tag{4.2}$$

$$\mathrm{PR} = 2^{-b} \tag{4.3}$$

$$\mathrm{LR} = 1 - PR \tag{4.4}$$

PR is the progress ratio, and LR is the learning rate. Typically, the progress ratio expresses the rate at which unit production cost (or price) declines for every doubling of cumulative production (experience). To elaborate, a progress ratio of 70% equals a learning rate of 30% and thus means that unit production cost would decline 30% and reach 70% value every time the production doubles. Initially, the values of the progress ratios are expected to be between 0 and 1 (or 0% to 100%). As the ratio gets closer to zero, the learning becomes more rapid while getting close to the value of one indicates lower rates of learning.

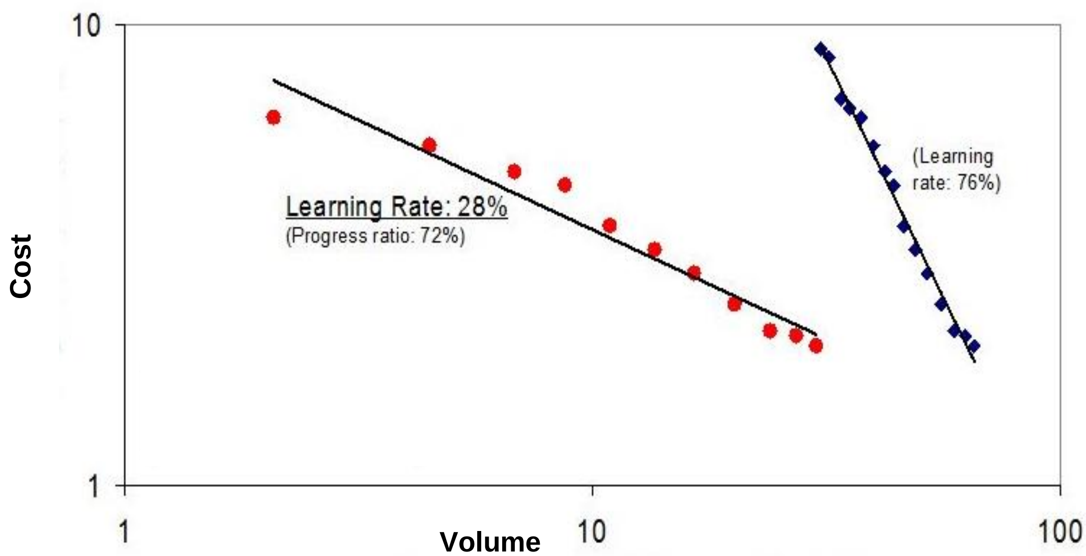

Figure 4.1: Simple graphical representation on learning rates versus progress ratios

Besides that, PR = 1 means there is no change at unit production cost. Also, PR > 1 indicates a cost increase[23] and a loss in efficiency as the total production increases (diminishing return instead of cost reduction and efficiency improvement). The learning rate might also change considerably depending on the data and data period used. This is one crucial issue to be aware of when one uses the experience curve

[23] Net cost increases may be observed when, for example, market tightness and commodity price increases offset the cost-reducing technology learning effects.

methodology (Wene, 2015). These observations may have important repercussions for the extent to which experience curves can be extrapolated in the future[24].

Graphically, the experience curve is typically described in a logarithmic scale as stated in equation 4.2. Figure 4.2 shows an example for a linear scale (left) and a log linear scale (right) experience curve:

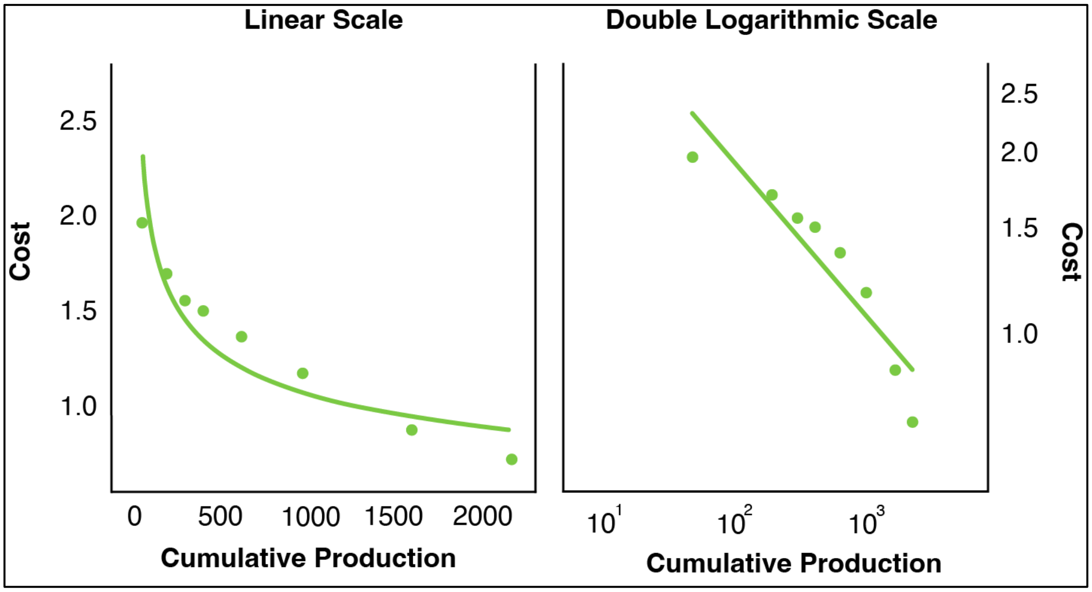

Figure 4.2: Linear scale versus log linear scale in experience curves

The basis for experience curves has been observed in empirical studies, as detailed in Chapter Three, but its theoretical foundations were first restricted to a much narrower interpretation focusing only on labour costs and within individual firms (Grafström & Poudineh, 2021; Henderson, 1984). As mentioned before, this has changed as total costs were considered thereafter in experience curve models (Muth, 1986; McDonald & Schrattenholzer, 2001; de La Tour et al., 2013). The empirical applications of the experience curve requires that choices must be made to build a robust model, which requires the analyst to deal with several measurement issues.

[24] See section 4.8.3 of this chapter for more details.

For example, the analyst must define the relevant product (service) market and measure the selected experience and costs (or prices). To date, no totally satisfactory approach to addressing these issues has been identified.

For some technologies, the experience (or learning) effect is less evident, or even non-existing (for hydrogen production or gas pipelines for example) (Schoots et al., 2008; van der Zwaan et al., 2011). In other cases, the experience curve relationship can be constructed but the statistical significance is low, and annual fluctuations in costs are high which affect the reliability of the model (Abdou & Mahmoud, 1977).

The use of the experience curve, as a conceptual tool in models, is widely accepted, however, it becomes more difficult when applied to evaluate the efficiency of various components while implementing an innovation policy[25]. (Ferioli, 2009). It is widely recognised that in many cases learning-by-doing may improve the overall costs or efficiency of a technology. It is, however, argued that, so far, insufficient attention has been devoted to studying the effects of single-component improvements, which, taken together, may explain an aggregated form of learning (Papineau, 2006; de la Tour, 2012).

For an entire technology, the phenomenon of learning-by-doing may possibly result from the learning of one or a few individual components only. The cost C of every industrial product can be expressed as the sum of the costs of its components, where each component is, in principle, characterised by a different learning parameter b (Abdou & Mahmoud, 1977; Louwen & Junginger, 2021). “If one assumes that the cost of each component decreases over time according to a power law relation, because of the learning-by-doing effect, it is thus possible to write the overall cost relation of a generic product as in which the index i represents a given cost component” (Ferioli, 2009). The question is that under what conditions it is possible to combine experience curves for single components to derive one comprehensive experience curve for the total product (Abdou & Mahmoud, 1977).

[25] An example of this is the evaluation of the market-pull versus technology-push mechanisms

A distinction between different types of innovation can help to alleviate this problem. It has been observed that incremental innovations remain well within the boundaries of the existing market and technologies/processes of an organisation, benefitting from the accumulated knowledge and innovation systems built up on (Auerswald et al., 2000; Bailey et al., 2011).

4.4 Sources of the Experience Effect:

Dutton and Thomas (1984) quoted Abell and Hammond (1979) who noted that "Experience does not cause [cost] reductions but rather provides an opportunity that alert managements can exploit." (Dutton & Thomas, 1984). Given that there is evidence to support the existence of an experience effect, the question arises on why this effect appears and what the driving factors are. The experience curve methodology quantifies an observed relationship without analytically disaggregates the individual driving factors (i.e., the shares caused by learning by searching, learning by doing, economies of scale, etc). The contribution of each of the underlying cost-reducing factors is likely to vary over time, depending on the phase of the innovation process.

When first introduced by Wright (1936) in the air frame industry, the learning by the assembly workers from the repetition of a complex task was considered to be the cause of this empirical relation, consequently, the experience curve model was adopted. Years later, Andress (1954) drew a distinction between experience in the literal sense as gained by worker and a whole series of other factors that include management decisions and innovations as a learning factor (Alchian, 1963; Henderson, 1984). A shortcoming of Andress' participation is that his observation was restricted to the aircraft industry. A possible support from electronic assembly and electro-machine products came from Conway and Schultz (1959) who argued that experience gained from repetition of the same task is not very important (Alchian, 1963).

Limiting the experience gained to learning from repetition will restrict the applicability of the experience curve to products and industries where this condition applies (Henderson, 1984). Therefore, Conway and Schultz (1959) gave more weight to other factors such as tooling, production methods, design and volume, improvement in quality, and the quality of managerial decisions (Conway et. al. 1959). Levy (1965) divided the sources of experience into three classes as planned, autonomous and exogenous learning (Levy, 1965). The first two correspond to the endogenous learning Conway and Schultz (1959) referred to in their paper, while the last one implies the improvement based on information acquired exogenously from the environment (Levy, 1965).

It is critical to understand the true reason behind the empirical relationship, and whether it is a correlation or a causation relationship between the model's components. For example, prices of raw materials and components produced by third parties may play an important role in the technology's cost determination. Market prices, however, are not a result of any direct experience gained. To better understand this, Ferioli et al. (2009) proposed to split up the technology costs into components and allocating the appropriate learning effect and learning rate to each cost component (Ferioli, 2009).

Several possible causes of this phenomenon have been discussed in the literature extensively, hence they remain controversial until now (Goddard, 1982; Day and Montgomery, 1983; Henderson, 1984; Alberth, 2006). Dutton and Thomas (Dutton & Thomas, 1984) described this phenomenon as an "aggregate empirical description" where underlying dynamics are masked (Dutton & Thomas, 1984).

Understanding the experience gain sources helps to strategically apply the experience curve model. It does so by allowing management to assess the performance of various sources, enhance the strong ones and mitigate the weak points (Dutton & Thomas, 1984). For example, if experience gains are vested in the current management and employees, management must focus on the personnel and compensation policies that take account of the need to maintain this human capital. Further, as Porter (1979) has noted, if costs are falling due to economies of scale- via more efficient, automated facilities and/or vertical integration, then cumulative volume may be unimportant to relative cost position.

Understanding the reasons why experience accumulates and cost declines in any given situation requires understanding the phase of the innovation process which are likely to vary over time (Bailey, 2011). These different phases in the historical cost development of the technology may lead to calculating different learning rates for the different phases, which would differ from a learning rate for the whole dataset (Wene, 2015).

There are three major sources identified in literature for the experience effect: learning, technological advances, and scale effects (Day & Montgomery, 1983). Beyond this point, it is recognised that "the experience curve phenomenon serves as a description of the evolution of an industry rather than specifying every possible cause of cost reduction and productivity increase" (Day & Montgomery, 1983). Day and Montgomery (1983) pointed out that it is difficult to distinguish between the contributions of scale, learning and technology. It is those major events that have been observed during the evolution and the diffusion of the industry. Most experience curves reflect the joint effects of learning, technological advances and scale (Hollander, 1965; Sahal, 1979).

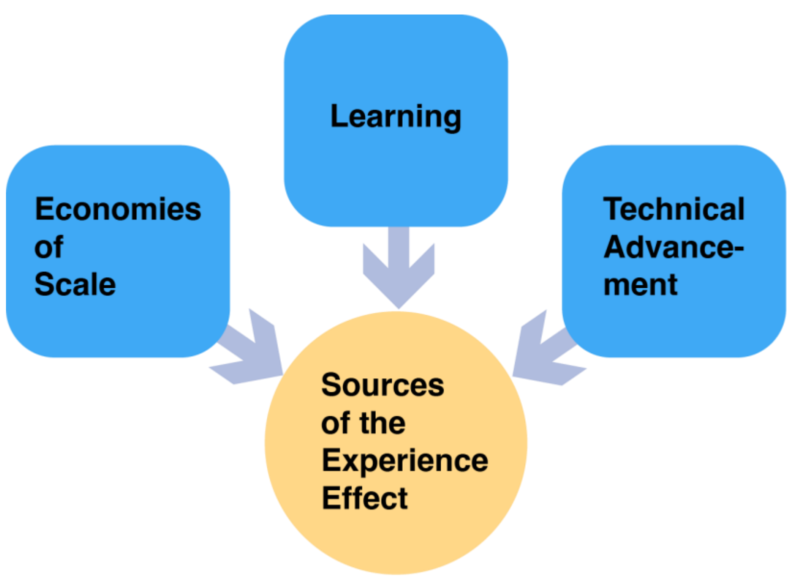

Figure 4.3: Sources of the experience effect

This standpoint is more relevant when the experience gain process is not fixed, and all sources of learning come from known minor improvements. In the higher levels, with more than subclass of learning, the experience gain mechanism becomes sophisticated in nature, and it gets more difficult to specify exactly who learns what (Sahal, 1979).

1. Learning

This might be termed the “practice effect,” which encloses the increase in efficiency of all aspects of labour input as a result of practice and the exercise of ingenuity and expertise (Sahal, 1979; Day & Montgomery, 1983). It includes the discovery of better ways to organise work through improved tools and work specialisation[26].

Also, the performance of production equipment will improve as workers become more familiar with them. The reason behind it is that with experience workers became more effective in using and maintaining the equipment and gained experience in the activity in question (Day & Montgomery, 1983).

It has been said that technologies do not learn, but organisations learn. It means that the enterprises producing and using the technology increase their capacity for effective action (Day & Montgomery, 1983). The observed learning-by-doing phenomenon is the result of a multitude of different cost reducing processes (Kahouli-Brahmi, 2008), including learning by doing (Arrow, 1962), learning by researching (Cohen and Levinthal, 1989), learning by using (Rosenberg, 1982), learning by scaling (Sahal, 1979) and learning by copying (i.e. knowledge spillovers)(Sagar and van der Zwaan, 2006). That been said, the effect of these underlying factors cannot be easily disentangled.

On technology spillover, it is observed that improvements within a certain technology often benefit from advances made in other fields, such as materials research or the benefits of military aircraft research that was fruitful for the development of the combined cycle gas turbine for example (Yelle, 1979).

[26] Doing one half as much, two times as often! (Day and Montgomery, 1983)

Accordingly, it is important to set the appropriate system boundaries to consider spill-over effects across sectors (Martinsen, 2011). Depending on the stage of the innovation chain, the system boundaries (as well as the regional boundaries) may change.

2. Technical Advancements

Innovation can take place on the technology supply side (i.e., production costs), as well as on the demand side (i.e., how and why end-users are using a technology). For some technologies (e.g., mobile phones, laptops, etc.), it may be easier to quantify the functionality than for other technologies.

In capital intensive industries, new production processes often contribute to the experience curve effect. Changes in the resource mix of technologies, such as automation replacing labour, also support a technology-driven base for the experience effect (Adler & Clark, 1991). Moreover, improvement through process and product changes participate in adding to the experience effect. This includes product redesign and standardisation (Basnet & Magee, 2016). It has been seen in the automobile industry for example by modularisation of the engine and transmission production that achieved economies of scale and participated to the experience effect. Nevertheless, the role of technical advancement in the experience effect is controversial. It was argued that technical advancement is the result of the accumulated experience, but do not cause it (Basnet & Magee, 2016).

3. Economies of Scale

Economies of scale take place when there is an increased efficiency due to size mainly (Alberth, 2006). It is defined as "reductions in average unit costs as output increases" (Healey & Grubler, 2015). It is another source of the experience curve effect, and it applies to the majority of investment and operating costs. Scale also enables other cost reduction activities. Thus, it creates the potential for volume discounts, vertical integration, and the division of labour which in turn facilitates learning (Healey & Grubler, 2015).

On the plant level, economies result from capital cost savings[27], an increased potential for division of labour, and better utilization of indivisible resources (Hollander, 1965). Forms of firm level scale economies include overhead economies (e.g., R&D and top management), economies in bulk handling (e.g., volume discounts), inventory economies, and marketing and financial economies (Ge et al., 2017).

According to Quinn (1981), scale seems relatively less important while technology and learning have major impact (Quinn, 1981). Quinn introduced a study Hollander (1965) who, in his book, "*The Sources of Increased Efficiency. A Study of DuPont Rayon Plants,*" found that the largest proportion of the technology driven cost reductions were due to minor technical changes suggesting adynamic process of small incremental change akin to Quinn's (1981) "logical incrementalism."

4.5 Which Costs?

All drivers in a business are intended for profit maximisation at the lowest cost possible. Cost characteristics of experience curves can be observed in all types of costs (Alberth, 2006). Technology learning could occur not only in investment costs, but in many other aspects of a technology such as conversion efficiency, maintenance costs, reliability, etc. (Nordhaus, 2009). Also, cost improvement of experience curves can be observed in all types of costs whether they are manufacturing costs, labour costs, marketing costs, development costs, overhead costs, etc. (Badiru, 1998).

Accordingly, the cost of production is vis-à-vis defined as the sum of the costs of individual operations (Muth, 1986). Nordhaus (2009) added that the total marginal costs of the experience curves are lower than current marginal costs; because an additional unit of output lowers all future costs as producers move down the experience curve (Nordhaus, 2009).

[27] As the scale of a plant increases, the capital costs increase less fast

These are among factors that determine costs, yet they may not be the most important factors. That decision, on which of these factors are most important, depends on which components dominate the cost structure of a technology. For example, for technologies where the costs are mostly determined by raw materials costs, such as steel, costs are mainly determined by market prices and not by learning effects (Gunawan, 2009). To understand which cost must be considered in the experience curve model analysis, cost analysis requires the assessment of the network of operations within a firm. Accordingly, the type of the cost analysed plays a role in the classification of the experience curve model mathematical relationship (Muth, 1986).

Further reading suggests that it is not agreed on in the literature whether to model variable cost, value-added cost, cash flow, or total cost. Brenneck (1959) suggested that the experience curve is supposed to be based on variable cost only. Brenneck argued that the only relevant costs to an experience curve calculation are those variable costs that fluctuate due to causes inherent in experience and learning (Brenneck, 1959).

Fixed costs are not reflected in the experience gain since they always move with the output: the greater the output, the smaller the fixed per-unit cost (Brenneck, 1959). They are seen irrelevant by a large group of analysts since dividing fixed costs by total production will always produce a decreasing curve as production increases. Abell & Hammond (1986) claimed that the correct costs to use are the total value-added costs. Conley added to this argument that to keep or to remove material costs is a relatively minor correction in most instances. Most of these arguments on costs are, unfortunately, conceptual without solid empirical evidence to support them in the relevant studies.

Observed costs may show large fluctuations in the short-term for different reasons. Among these are changes in the level of capacity utilisation, new production methods wage settlement and others (Papineau, 2006; de La Tour, 2013). However, these tend to smooth out after a certain period at the long-term. Cost fluctuations on the short-term explains the recommendation made by many researchers to use experience curves for long-term strategic planning and cost forecasting as short-term forecasts can be illusive. This is one reason why it is recommended to have both a short- and long-term experience curves, where possible, to compare results from both models and see what each timeframe tells about the future.

4.5.1 Using Price as a Proxy for Cost

Despite the recommendation that technology learning should be measured by cost rather than price, reliable cost data on the industrial level are often difficult to obtain and the experience curve literature usually measures the learning effect on this level by price series (Alberth, 2006; Nagy, 2013; Moore, 2015; Boone, 2018; Rypdal, 2018). It is therefore crucial to clarify the relationship between cost and price. The Boston Consulting Group (BCG)(1968), The international Energy Agency (IEA)(2000), Junginger et al. (2010) discussed the complications in analysing price time series to obtain experience curves. The Boston Consulting Group (BCG)(1968) argued that the ratio between price and cost remains constant in equilibrium markets, i.e. performance measured by price and cost has the same learning rates in this case. However, market disequilibrium may initiate price–cost cycles, which show up as systematic deviations between costs and prices.

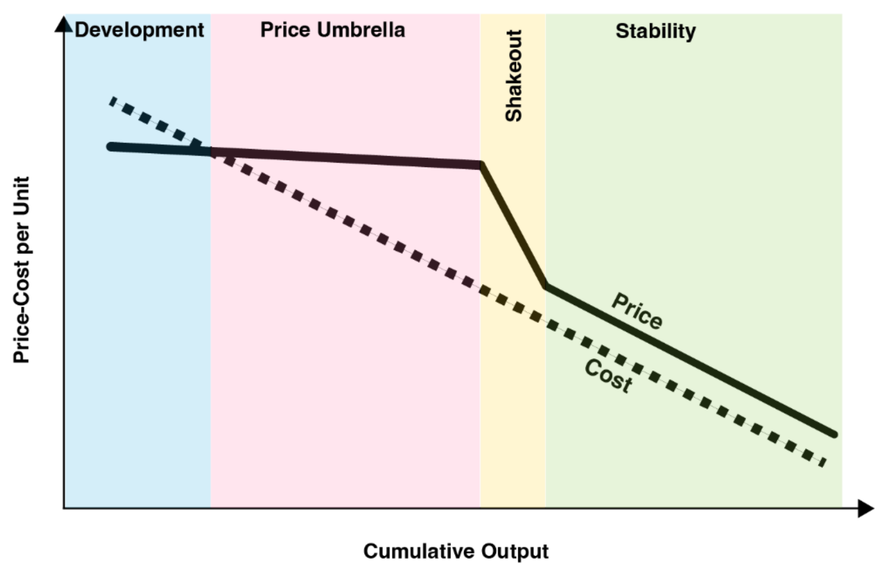

Figure 4.4: Price-cost relationship at different phases of a technology's life cycle (Source: BCG, 1968)

This observation by the Boston Consulting Group (BCG) was supported by the leading study conducted by Dutton and Thomas (1984), who compiled 108 cases of cost experience curves measured in firms and include manufacturing processes in a wide selection of industries. This resulted in a distribution of learning rates that showed a broad peak around 20%. Measurements of price experience curves show the *same distribution*, lending support to the earlier interpretation given by the Boston Consulting Group (Dutton and Thomas, 1984).

Prices are typically set below cost to establish a market. In pre-commercial and niche market stages, prices may be set lower than costs in expectation of large profits during the phase of pervasive diffusion. As volume and experience reduce cost, the prices are maintained, which should gradually convert the negative margin to a positive one. If market structure permits, prices are not reduced at the same rate as costs fall at potentially early maturity, where all producers are inclined to use an optimal combination of the total cost and profit margin to stay in the market (Henderson, 1968; Henderson, 1984; Nemet, 2006; Papineau, 2006; Neij, 2008; Elshurafa et al., 2018).

Typically, experience curves describe the development of production costs, as a function of accumulated produced volume. Market prices, however, determine the actual diffusion of technologies. Prices can often differ strongly from the actual production costs, which are accounted for by modelling the supply and demand in the market (Bass, 1980; Neij, 1997). It could also lead to the problem of price data which is sometimes used in modelling (as it can be easier to collect) not equating to cost data (that could be confidential and difficult to obtain). Still, cost data may include some components that are purchased from third parties and therefore have their own price effects as well.

4.5.2 Floor Costs

The concept of floor-costs has also been present in the experience curve discussion. Efforts have been made to calculate their value with respect to minimum material costs for a specific technology (Alberth, 2006; Papineau, 2006). The existence of floor costs calculations was not always as accurate as these calculations are mainly based on engineering perceptions only (Alberth, 2006). Although this engineering perception makes sense in terms of explaining past cost (or price) trends, it may not necessarily be accurate when forecasting future costs where new challenges may arise.

Over the years, the question whether the future cost should be limited by a floor cost, or an absolute lower limit to production costs, persisted. On the one hand, it has the advantage of reducing the likelihood of overestimating the technology cost reduction potentials (Alberth, 2006). On the other hand, however, floor costs may be conservative estimates and may hide opportunities and conserve status quo (Candelise et al., 2013).

4.5.3 Company, Industry, or Global Cost Curve?

An important question to answer is whether technological learning for a specific technology is a global phenomenon, or learning simply develops at different rates due to company or regional specific factors (Day & Montgomery, 1983). Answering this question will have an important impact on the choice of models (global vs. regional) that are suited for endogenously simulating learning.

The answer is: it depends. In general, a global approach is advised if the technology (e.g., a wind turbine, solar PV modules) is the same in all countries (Abdou & Mahmoud, 1977). If so, this leads to a globally defined learning rate for this technology (Papineau, 2006; Wene, 2015). In the global marketplace for some technologies there can be development and production in one region and installation in another (for example wind turbines are produced in Denmark installed in Asian countries). However, cost components relying on local skills and or embedded in local institutions, such as the installation of PV systems on buildings, may not find its way to other regions. This, accordingly, blurs the regional differences and complicates data collection (Schilling & Esmundo, 2009; Candelise et al., 2013; de La Tour et al., 2013).

Simultaneously, clustering of industries or companies could help driving faster innovation at specific sites that could lead to regional differences in learning rates (Eising et al., 2020). Fuel ethanol from sugarcane in Brazil between (1975-1995) is one example. However, any regional diversity in technology economic and technical performance is likely to be short lived. This is due to the realisation that the superior technology will either conquer or be imitated and thus disperse to all regions (Elshurafa et al., 2018).

Louwen (2021) supported the establishment of experience curves would represent a whole industry of a technology, rather than a single company. This is conditioned, according to Louwen, upon using experience curves that include total costs of production, not just labour (Louwen, 2021). Day and Montgomery (1983) also emphasised that a single industry price may be misleading if it requires averaging across disparate models, features, and accessories, or when competitors use markedly different strategies such as full service vs. bare—bones product offerings (Day and Montgomery, 1983).

4.5.4 Dynamic vs Static Costs

The total cost, the left-hand side variable, in the experience curve estimation could be too general which might result in insignificant results. What the equation measures is very important and affects the quality of the estimate as previously emphasised. To explain this, Dutton and Thomas (1984) have pointed out the difference between ‘dynamic’ and ‘static’ economies (Dutton & Thomas, 1984).

According to Papineau (2006), dynamic economies bring a downward shift in the cost curve by continuous change, whereas static economies cause a movement along the cost curve. This difference is important as static economies can be reversed and cost can increase again if output decreases (Papineau, 2006). However, if the cost reduction has occurred due to experience, that means the curve has shifted downward and fluctuations in output across manufacturers is less likely to affect the cost curve.

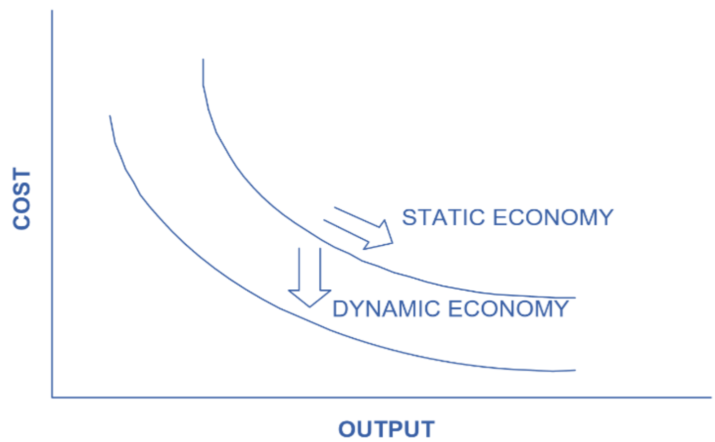

Figure 4.5: Cost curve shifts versus moving down the curve (Source: Papineau, 2006)

That been said, most experience curve models have fluctuating static economies embedded in them, coupled with the absence of dynamic economies, which affected the statistical significance of the models (Dutton et al., 1984; Papineau, 2006). This identification issue has been controversial for so long in literature. However, Papineau (2006) correctly claimed that when these issues are pointed out in literature, they have generally been 'relegated' briefly, leaving the bulk of information and treatment of this to the references (Papineau, 2006).

4.6 Experience Curves Characteristics: Empirical Issues

According to Alberth (2006), empirical evidence on experience curves was first discovered in 1925 at the Wright-Patterson Air Force Base. They found that plotting an aeroplane's manufacturing input against cumulative number of planes built on a log-log scale produced a linear result (Alberth, 2006). Following Wright's observation in 1936, the next major advancement, reported in experience curves empirical literature, was made by Arrow in his 1962 publication (Arrow 1962, IEA 2000). He generalised the learning concept and put forward the idea that technical learning was a result of experience gained through engaging in the activity itself. Undertaking an activity, Arrow's suggestion would lead to a situation where only "favourable responses are selected over time," (Arrow, 1962). Söderholm and Sundqvist (2007) discussed econometric aspects of experience curves, and the potential impact of quantifying and interpreting the scale effect on the reliability of the curve (Söderholm and Sundqvist, 2007). Yu et al., (2011) questioned the importance and the consequences of including more than one factor, such as input prices and/or scale-effects, in the experience curve calculations (Yu et al., 2011).

Jamasb and Köhler (2008), have contributed with a broad critical assessment on the empirical aspects of the experience curve. Ek and Söderholm, (2013) added a good review of some of the key challenges in measuring technology learning in the wind power sector. Nordhaus (2014) emphasised, however, that a statistical identification problem is present when one tries to separate learning from exogenous technological change, which creates upward biases in learning estimations. Nordhaus (2014) reported erroneous estimates of the total marginal cost of output which would introduce bias in optimisation models. Odam and de Vries (2020) echoed Nordhaus concerns on potential problems with experience curve estimation, concluding that experience curves *should be interpreted with prudence* (Jamasb & Köhler, 2008; Ek and Söderholm, 2013; Nordhaus, 2014; Odam and de Vries, 2020).

Montgomery and Day (1983) argued that much of the empirical evidence in support of the experience curve phenomenon has been graphical in nature (Day & Montgomery, 1983). Despite the empirical support and the advantages of experience curves, "acceptance is waning," said Montgomery and Day (Day and

Montgomery, 1983). They argued that the evidence has not focused on the measurement and econometric issues which would be required for a more scientific assessment. Accordingly, the empirical applicability of the experience curves to predict the future costs of technologies has an applicability test in real world scenarios. The main empirical considerations concentrated around three main issues: first, assuming a constant learning rate parameter within linear models. Second, the determinants of the variable(s) used as a proxy for experience. And third, the correct number of independent variables that should be used in building the model.

This section is an introduction to the types of experience curves in regard to the number of factors used in the model. It summarises the methodological background of both the One-Factor and the Two-Factor-Experience Curve concepts and investigates possibilities for further refining them. For both concepts it looks into methodological challenges, uncertainties in parameters and data availability.

4.6.1 Single-Factor and Multi-Factors Experience Curves:

The one-factor form of the experience curve uses only experience as the independent variable to explain cost changes over time (de La Tour et al., 2013). It is the traditional and most-common experience curve model that utilises the cumulative output of the technology as a proxy for overall experience gains and results in an aggregated learning rate (LR) estimate. Alberth (2006) discussed reasons behind the Single Factor Experience Curve (SFEC) popularity and referred this to the simplicity of its use. Nevertheless, Goddard (1982) and de La Tour (2012) reported drawbacks from using one factor model to represent the experience effect such as the presence of the omitted variable bias which occurs when a statistical model leaves out one or more relevant variables (Goddard, 1982; de la Tour, 2012).

Also, Neij (2008) claimed that using experience as the only explanatory variable does not allow any flexibility in the pace at which cost decreases with cumulative production, which can be inconsistent with economic theory (Neij, 2008). Accordingly, Alberth (2006), Neij (2008), and de La Tour (2013) have supported the construction of multi-factor experience curves (MFEC) and the associated learning rates (Alberth, 2006; Neij, 2008; de la Tour, 2012). The logic behind this curve is to identify and isolate the combined effect of separate learning factors. This approach would help to derive a “true” learning rate according to Alberth (2006). It also assures the consideration of other learning mechanisms like R&D, scale effects and others (Neij, 2008; de la Tour, 2012). When using multi-factor experience curve models, the learning rate is more sensitive towards the consideration of the factors. Accordingly, lower learning rates are reported with MFECs which indicates a likely positive bias in the single factor experience curve (SFEC) outcomes that causes higher unrealistic learning rates.

Single Factor Experience Curves (SFEC) generally calculates higher learning rates which indicates a possible bias in the results (Alberth, 2006; de la Tour, 2012). However, there are no enough studies using Multi Factor Experience Curve (MFEC) models to make a concrete conclusion in regards to this point. In fact, there are “few” MFEC studies in comparison to the SFEC ones (de la Tour, 2012).

(a) Single Factor Experience Curve (SFEC):

As presented in equation 4.1**,** the Single Factor Experience Curve (SFEC) relates the unit cost (price) development of a technology to the evolution of one factor, the accumulated learning, classically represented by accumulated production. It is illustrated by plotting a reduction in technology costs (or prices) against its accumulated production (Candelise et al., 2013).

The unit cost development observed with Single Factor Experience Curve (SFEC) – in which costs reduce by a constant fraction for each doubling of cumulative production – can be described by a power law. The power law behaviour makes it possible to plot experience curves as a straight line on a double-logarithmic scale (Goddard, 1982). Once a learning rate has been calculated the interest for the analyst is to use this learning rate to model and analyse future cost developments.

Despite some annual fluctuations, there is a good reliable match between the real cost data of PV and the cumulative installed volume. Moreover, extrapolating the line further gives an indication about the capacity at which a certain cost level could be reached.

Using Single Factor Experience Curve (SFEC) benefits from relatively easily accessible data (Alberth, 2006). Investment costs (prices) and production (or installation) volumes are often well recorded compared to other underlying cost drivers, and thus reliable experience curves can be determined for cost forecasting purposes (Nemet, 2006).

Among challenges that faces the application of the Single Factor Experience Curve (SFEC) is the technological learning evidence. For a number of technologies, the learning effect is less evident than for the case of PV for example. As for hydrogen production or gas pipelines, it is non-existing (Schoots et al., 2008; van der Zwaan et al., 2011).

In other cases, the SFEC can be constructed but with low statistical significance, and high annual fluctuations in costs (Nemet, 2006). Also, net cost increases may be observed when e.g. market tightness and commodity price increases offset the cost-reducing technology learning effects (Alberth, 2006). If historical costs are analysed on this partial-learning basis, the analysis could derive vastly different learning rates and results and achieve a better match with statistical data (Nagy, 2013; Louwen, 2021).

One of the strengths the Single Factor Experience Curve (SFEC) has is that it simplifies cost dynamics. This is because it groups several underlying drivers of cost reduction in one factor that matches empirical data (Henderson, 1984).

On the other hand, this high level of aggregation is a major criticism of the Single Factor Experience Curve (SFEC) concept, because it does not allow the analyst to quantitatively associate the observed cost (price) reductions to individual drivers such as learning-by-research, learning-by-doing or learning-by-investments (Chu & Zhang, 2003, Nemet, 2006). This makes it hard to provide a clear quantitative assessment of the impact of a policy option that addresses just one of these factors, such as R&D investments (Alberth, 2006).

In fact, the Single Factor Experience Curve (SFEC) has been constantly criticised (see for example Neij, 2003; Nemet, 2006; Nordhaus, 2009; Holmes, 2010) due to the uncertainties associated to the lack and treatment of data, and the aggregated approach to innovation mentioned above. In particular, it is considered problematic from a methodological viewpoint as well as from a data point of view, which may lead to an overestimation of the learning effect.

Despite uncertainties and criticism, the Single Factor Experience Curve has proven to be a useful framework for empirically evaluating technology cost evolutions. However, a split of the Single Factor Experience Curve (SFEC) into a Multi Factor Experience Curve (MFEC) has been undertaken by Kouvaritakis et al. (2000) and others to tackle the model's uncertainties.

The Multi Factor Experience Curve (MFEC) approach tries exactly to do this – in order to better assess the impact of diverse cost-reducing drivers, it separates out the effects of learning-by-doing and learning-by-searching as explained below.

(b) Multi Factor Experience Curve (MFEC):

Nemet (2006) and Nordhaus (2009) provided critique directly relevant for diagnosis and design the experience curve model. Both, Nemet and Nordhaus, argued that most of observable learning is due to well-known processes such as R&D and economies of scale (Nemet, 2006; Nordhaus, 2009). Thus, ignoring these causes in measuring learning leads to erroneous estimation of future estimations of future technology costs.

Accordingly, the Mutil Factor Experience Curve (MFEC) models were introduced in literature. The Multi Factor Experience Curve (MFEC) approach tries to disentangle the diverse underlying drivers of technology cost reduction (Nemet, 2006). This helps to assess the impact of diverse cost-reducing drivers, and it separates out the effects of different factors such as learning-by-doing and learning-by-searching. However, learning by doing and learning by searching cannot be easily satisfactorily separated. And certainly, the one factor cannot substitute the other (Nordhaus, 2009).

In addition to the previously mentioned factors, market prices of raw materials and components produced by third parties may also play an important role in the technology's cost dynamics such Silicon prices in solar PV modules manufacturing (de La Tour et al., 2013). To better address this, Ferioli et al. (2009) proposed to split up the technology costs into components and allocating the appropriate learning effect and learning rate to each cost component.

Nemet (2006) analysed seven factors which are assumed to explain the cost development, which among them include module efficiency, plant size, silicon cost, and yield. Research and Development (R&D), improves module efficiency, plant size represents economies-of-scale, and silicon cost is an input factor. Nemet's model performs poorly for the period from 1975 until 2001. The seven examined factors explained less than 60% of the cost reduction, where the most important factors being efficiency, plant size, and silicon cost (Nemet, 2006).

However, applying the model separately between 1975–1979 and 1980–2001 provides interesting results. For the first period, the model performed worse with 59% of the change remains unexplained. For the second period, there was a significant improvement in the model's performance leaving only 5% of the cost decrease unexplained (Nemet, 2006). The author linked this to a drastic market change over this period (e.g., space applications to terrestrial applications).

Some studies restricted the Multi Factor Experience Curve (MFEC) model to public R&D investments to removes many methodological concerns without reducing its usefulness for policy. To further investigate this approach, Klaassen el al. (2005) analysed the effect of public R&D on wind energy in Denmark, Germany and the UK. Popp, Santen et al. (2012) have proposed using patent counts as a proxy for knowledge stock rather than R&D budgets. Patent counts are a closer indication of innovation and the data is relatively accessible, while knowledge spillovers between technologies can also be measured through patents (Santen et al.; 2012).

There is criticism to the proxies used for the knowledge stock, and to the output function. The focus of Research and Development (R&D) does not necessarily lie on investment costs but on technological improvements such as efficiency, maintenance, safety and other factors, both technological and non-technological (Nordhaus, 2009). Hence, to use investment costs as the sole output of R&D is a misrepresentation, similar to the aggregation point made for the Single Factor Experience Curve (SFEC).

Moreover, the data on R&D investment is confidential and scarce, in particular when a high level of technological disaggregation or private sector investment is needed (Candelise et al., 2013). In the energy field, the International Energy Association (IEA) RD&D statistics represents a good source of information on energy RD&D budget from its member countries only[28]. This dataset is a useful starting point that reflects public R&D investments. Data on corporate R&D expenditure are more difficult to obtain due to confidentiality, in particular when focusing on the R&D expenditure by technology (Jacquier-Roux and Bourgeois, 2002; De Nigris et al., 2008; van Beeck et al., 2009). Furthermore, even if data were available, attention needs to be paid to the fact that companies may often over- or underestimate them for strategic planning purposes (Jacquier-Roux and Bourgeois, 2002; Gioria, 2007).

These arguments raised two counterclaims at the organisation level of the learning system analysis: first, the distinction between public and private (industrial) R&D is crucial for understanding technology learning, and second, 'public R&D can seed the learning process within the industry but not directly influence total cost' (Alberth, 2006; Papineau, 2006).

[28] Despite some related uncertainties that originate from data gaps and differences in the extent to which individual member countries include regional funding, institutional budgets and support to demonstration activities in the data submitted to the IEA (Wiesenthal et al., 2012)

That been said, the question arises on whether it will be better to use exogenous assumptions on future R&D investment levels, or to endogenise the calculation in the model. The advantage of the latter is that consistent scenarios could be produced, and data gaps would be filled. On the contrary, an endogenous calculation of corporate Research and Development (R&D), by assuming a constant R&D intensity multiplied with the sector's turnover, implies a risk of exaggerating lock-in effects for certain technologies, as with this method increased technology ingestion would not only lead to learning by doing but also to increased corporate R&D funding levels (Jacquier-Roux and Bourgeois, 2002; Nemet, 2006; Gioria, 2007). For the most part, in the absence of a model simulating business Research and development (R&D) budgeting on the basis of risk and expectation, it has been commonly advised to leave R&D funding exogenously determined by considerations derived from the technology perspective analysis (Alberth, 2006).

Nemet (2012) led a leading study to examine the impact of adding more factors to the experience curve model. Nemet concluded that "a much broader set of influences than experience alone contributed to the rapid reductions in the past" (Nemet, 2012). While these refinements to the (MFEC) may help reassess the traditional learning concept that masks underlying trends, they may cause problems with data availability associated to quantifying all the parts of the total cost.

4.6.2 The Shape of the Experience Curve:

Historically, a number of authors have suggested several models for the shape of an experience curve, especially deviations from the conventional log-linear (Equation 4.1) at the beginning and tail end of the curve. Forecasting with an experience curve requires selecting an appropriate model, which is as crucial as accurately estimating parameters (Martino, 2003; Schilling & Esmundo, 2009; Yeh & Rubin, 2012; Elshurafa et al., 2018; Rypdal, 2018). Using an inappropriate model can result in seriously unreliable forecasts (Martino, 2003; Chu, Wu, Kao, & Yen, 2009; Yamakawa, Rees, Salas, & Alva, 2013).

The conventional experience curve model is not the only model that describes the relationship between cumulative unit numbers and production cost (Yelle, 1979). Several geometric forms of the experience curve model have been suggested since Wright's paper (1936). Garg and Milliman (1961) reported the importance of studying the possibility that any other specification could fit a model better (Garg and Milliman, 1961). Among well-known models in this field are: (1) The log-linear model, (2) The plateau model, (3) The Stanford-B model, (4) The DeJong Model, and (5) The S-curve model (i.e.: cubic L-C), as shown in Figure 4.6:

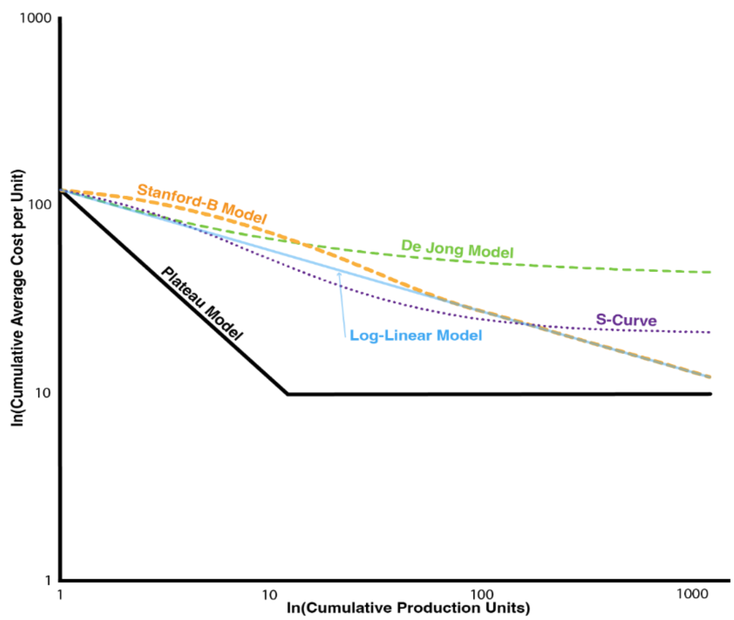

Figure 4.6: Geometric shapes of the experience curve

There is strong empirical evidence in literature that experience curves adhere to power law models (Wright, 1936; Henderson, 1984; Papineau, 2006; Swanson, 2006; Badiru, 2012). However, Carr (1946), Dutton and Thomas (1984), Schilling and Esmundo (2009), Wene (2015), Hansen (2017) and Hogan (2020) confirmed that many technologies exhibit an S-curve in their performance improvement over their lifetimes (Foster, 1986; Twiss, 1992; Christensen, 1993, 1994; Ayres, 1994; Schilling & Esmundo, 2009). Carr (1946) was among first who stated that growth is rarely linear and linear models do not provide the best fit for the learning process. Carr (1946) and Conway and Schultz (1959) initially reported this phenomenon and Baloff (1966, 1971) later researched it in depth as mentioned earlier.

This S-shape for a particular product or technology can be predicted using different technology forecasting methods that are appropriate for time series data as described in section 2.3 of this chapter. These models help the modeller to identify the time required for a specific technology adoption, and what might be the maximum penetration (Hogan et al., 2020).

In reality, the logic behind non-linear experience curve shapes is that cost reduction cannot be achieved for a technology endlessly[29]. The performance of a technology typically shows slow initial improvement, followed by rapid growth, then diminishing improvement when plotted against the amount of effort and/or money invested. At the early stages of a technology, the fundamentals of the technology are poorly understood which explains the slow performance improvements. Once scientists or firms gain a deeper understanding of the technology, improvement begins to accelerate. As the technology begins to reach its limits, the cost of each marginal improvement increases, and the S-curve flattens out. Grübler (2006) partially agreed with this observation and argued that technology cost reduction happens quite fast in the early stage of the development process, but the potential for cost reduction declines drastically as the technology matures.

A key concept in experience curve estimation and modelling is the idea of a plateauing curve (Carlson, 1961; Yelle, 1979; Badiru, 2012; Honious et al., 2016; Boone, 2018). Yelle (1979), Badiru (1998), McDonald and Schutzer (2000) found reasons to search for something other than Wright's log-linear model and discussed the plateau effect in different industries.

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[29] One could imagine a minimum fixed cost necessary to build and deliver the technology, fulfilling technical and economic constraints. This minimum cost is referred to as technology floor cost that is commonly imposed in cost models to prevent the technology costs falling below a specified value.

Plateauing, or the "plateau effect", phenomenon typically indicates the lack of any improvement with additional manufacturing. Plateauing was studied by Baloff (1966) in machine-intensive manufacturing. Plateauing was observed in twenty out of twenty-eight cases. As for labour-intensive manufacturing, plateauing was slower and less evident according to Baloff. This general conclusion was confirmed by Yelle (1979) that plateauing is much more likely to occur in machine-intensive industries than in labour-intensive industries (Yelle, 1979)[30]. It is also clearly observed in Hirschman's (1964) data relating to the electric power industry. Hirschman (1964) wrote that the experience curve effect is prevalent even in machine-intensive industries, and that a similar relationship suggesting experience curves were seen in the entire industries of petroleum refining, electric power, and steel.

Yelle (1979) offers the following reasons for the presence of the plateauing effect in the machine-intensive industry: (i) The higher proportion of machine-paced labour to total labour (ii) Management's unwillingness to invest more capital in order to acquire the technological improvements necessary for the learning process to continue (iii) Skepticism on the part of management that new goals are not set once previously defined goals have been achieved. Following on Yelle's point of view, it is clear that management's decisions are responsible for the unlearning and relearning in the machine-intensive industries. In other words, to overcome plateauing in machine-intensive industries and continue the learning curve effect, management should play a much larger role than the labours.

The flattening effect was further explored and compared to Wright's conventional model in many studies published by the *Air Force institute of Technology* (AFIT) by Badiru (2012), Moore (2015), Johnson (2016) and Boone (2018). Badiru (2012) concluded that forgetting was important to factor into an experience curve evaluation and that half-life analysis is important to consider when estimating the effects of the experience curve. The concept of half-life, as named by Badiru, is "the amount of time it takes for a quantity to diminish to half of its original size through natural processes," (Badiru, 2012).

[30] This observation is particularly important for this thesis when discussing the solar PV industry as a machine-intensive industry.

Forgetting in the production process can be caused by both internal and external factor (Badiru, 2012). Internal events can range from complacency of the workforce to policy changes. On the other hand, external factors include anything from natural disasters to drastic market swings that cause a halt in production. Badiru (2012) focused on the actual phenomenon of learning that is apparent in production and less on how the government can use that analysis to generate accurate cost estimates.

Forgetting, in general, implies that an organisation will experience a decline in performance over time as a result of factors such as lack of training, reduced skills and natural forgetting (Badiru, 2012). The concept of forgetting and its impact on non-constant learning rates has proven relevant in contemporary experience curve research (Hogan, 2020).

The plateauing phenomenon is a closely connected concept in the contemporary models' analysis. Jaber (2019) stated that "plateauing occurs when the learning process ceases and manufacturing enters a production steady state" (Jaber, 2019). When the plateauing occurs, it results in a flattening, or partial flattening, of the experience curve corresponding to a zero – or near zero – learning rates (Jaber, 2019; Hogan, 2020). However, nonlinear models usually include a linear phase before they complete their life cycle. That implies that most *linear models are just incomplete non-linear models* that need more time to mature.

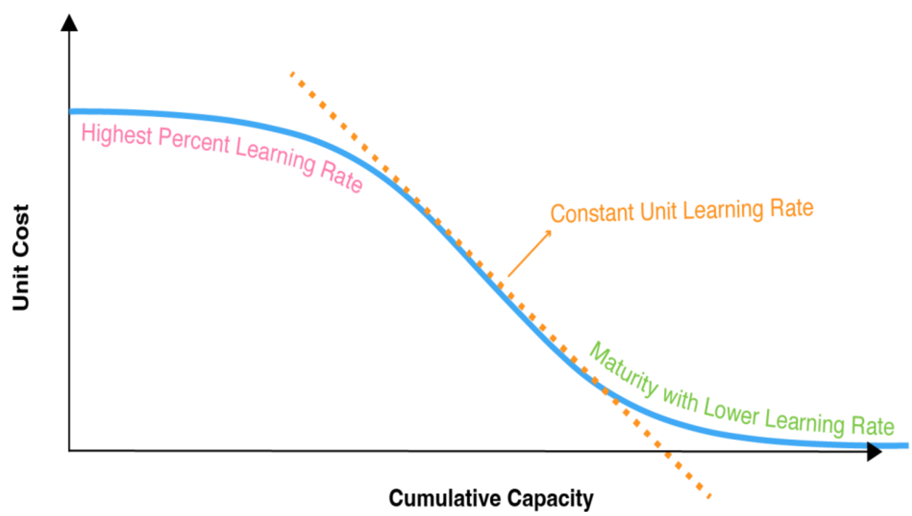

Figure 4.7: The plateauing phase in contemporary experience curves

Empirical studies have shown experience curves to exhibit diminishing learning rates. However, this behaviour in the experience curves context has not been well explored in empirical literature. Recently, Badiru (2012), Moore (2015) and Boone (2018) analysed the performance of contemporary Stanford-B, DeJong and S-curve models in airframe industry. Their research provided insight into how the traditional learning curve models become less accurate at the tail-end of production (Badiru, 2012; Moore, 2015; Boone, 2018).

Johnson (2016) followed up on Moore's research (2015) and analysed the plateau effect as well. Johnson hypothesised that there was a flattening effect at the end of the production process and that learning does not continue to happen at a constant rate toward the end of a production cycle. Johnson also states, "it is human nature for people to lose focus or concentration at certain times when performing repetitive tasks" (Johnson, 2016).

There are a number of limitations of using the S-curve model as a prescriptive tool. First, it is rare that the true limits of a technology are known in advance, and there is often considerable disagreement among firms about what the limits of a technology will be. Second, the shape of a technology's S-curve is not set, simply, in stone. Unexpected changes in the market, input prices, component technologies, or complementary technologies can shorten or extend the lifecycle of a technology. Furthermore, firms can actively influence the shape of the S-curve through the nature of their development activities (Jarne et al., 2015; Shukla et al., 2015; Hogan et al., 2020).

In their famous study, Yeh and Rubin (2012) concluded that the shape of experience curve and the magnitude of learning rates are uncertain and that the consequences of these uncertainties for policy need to be explored (Yeh & Rubin, 2012).

Nonlinear curves of technological improvement have been well documented in a wide range of industries, including disk drives, automobiles, sailing ships, semiconductors, vacuum tubes, steam engines, and more (Foster, 1986; Ayres, 1994; Nagy, 2012). However, it is less used and discussed in literature compared to the linear models.

When it comes, for example, to the S-curve nonlinear models, 53% of articles in the Journal of technological forecasting and social change, didn't mention S-curves at all between 2002 and 2007. Only 4% of the articles that mentioned the S-curves were about the characteristics of S-curves applications. Between 1996 and 2006, more than 1300 articles were written on technology forecasting, where only 11 papers report some trials to apply quantitative S-curve analysis in the technology forecasting context. Recent work started using and testing nonlinear models more as more dynamic models to generate technology cost forecasts. A brief historical overview on the models used for comparison in this research is given in the following section:

a. The Gompertz Model

The Gompertz function is a sigmoid curve, which describes asymptotic growth as being the slowest at the end of a given time period or at the maximum of a given variable (Akın et al., 2020). This curve has an S-shape which is non-symmetrical. It assumes that the period of increasing growth is shorter than the period in which this growth is decreasing, and in which the process is adjusting to its saturation level (Franses, 1994). The model was first suggested and first applied by Benjamin Gompertz in 1825. Since then, it became well-known and widely used in many aspects of science (Jarne et al., 2015). Researchers have fitted the Gompertz model to almost everything from biology to plant growth, tumour growth, and demand forecast with enormous literature.

In its simplest form, the basic Gompertz growth model can be represented by the equation:

$$Y(t) = Le^{-ae^{-bt}} \tag{4.5}$$

Where:

Y(t) – Expected value (mass, length, population) at time t

t - Time period

L – Upper Asymptote (Maximum population, mass, length possible)

a – Regression coefficient

b – Growth Rate

The first attempt to use a least-squares method for the Gompertz model to find the best curve, was attempted early in literature (Franses, 1994; Buchanan et al., 1997). Until the 1940s, it was done by log-transforming the values to make it easier to determine the sum of squares (Jarne et al., 2015). The saturation level is one of the three unknown parameters in the model. Its value is typically assumed a priori or estimated iteratively. This value plays a central role in the forecasting of future values of a specific time series. To improve the estimation, Gibson, Bratchell, and Roberts (1987, 1988) proposed a four-parameter Gompertz model by adding a constant term β to the ordinary Gompertz model Equation.

b. The Logistic Model

The logistic curve was applied for the first time by Verhulst, who published his research in 1838 in the journal "Correspondence Mathematique et Physique". Almost a century later, in 1920, R. Pearl and L.J. Reed rediscovered the logistic curve in the course of their study of the evolution of fly populations.

The Logistic model has often been used in the fields of demographics, biology and economics, to describe the evolution of populations and to model processes of dissemination and self-organization associated with the spread of new technologies and products, technological change and, in general, economic growth. The

Logistic model has proved applicable to technology driven diffusion and adoptions where new technology displaces old technology because it is technically and economically superior (Muraleedharakurup et al., 2010). The Logistic growth model can be represented by the equation:

$$Y(t) = L/\left(1+ae^{-bt}\right) \tag{4.6}$$

Where:

Y(t) – Expected value (mass, length, population) at time t

t - Time period

L – Upper Asymptote (Maximum population, mass, length possible)

a – Slope factor

b – Growth rate

The very symmetry of the logistic curve means that the period of expansion is equal to that of contraction, while in the Gompertz curve the period of acceleration is shorter than that of deceleration (Muraleedharakurup et al., 2010).

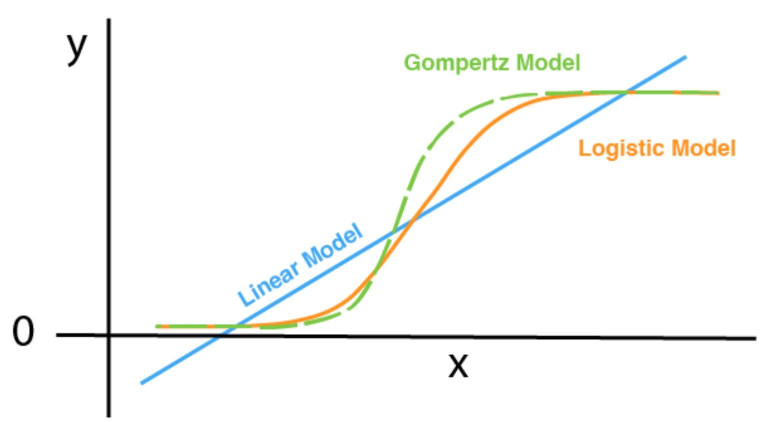

Figure 4.8: Graphical representation of Gompertz and the Logistic models

To summarise, both Gompertz and the Logistic models challenge the implicit assumption in the traditional experience curve theories that learning obtained through experience does not depreciate. Empirical evidence demonstrates that learning depreciates at both the individual and the organisational levels. Gompertz and the Logistic models make use of the concept of performance decay (commonly called forgetting or plateauing) to model non-constant learning rates (Hogan, 2020).

One goal of this research is to examine the accuracy of Gompertz and the Logistic models in comparison to the conventional Wright's model. The Gompaertz and the Logistic were originally used as growth curve, and they have the form of a sigmoid, where the initial exponential growth converges to a maximum value due to a nonlinear saturation mechanism. Both models possess similar properties that make them useful in both growth and experience curve studies. It does not appear that either curve has any substantial advantage over the other in the range of phenomena which it will fit (Akın et al., 2020).

However, the point of inflection of the Logistic model is equivalent to the point of maximum deployment (Franses, 1994). Symmetrical models have a fixed point of inflection where the growth and decline are symmetrical around this point (Malyusz & Pem, 2014). On the other hand, asymmetrical models have their inflection point at less than 50% with a faster growth than decline. Therefore, this research examines the impact of this feature on the accuracy of the forecasting models.

Another difference between Gompertz and the Logistic models is that growth rate declines *linearly* in the Logistic model, while it declines *exponentially* in Gompertz model (Franses, 1994; Buchanan et al., 1997; Akın et al., 2020). This difference could potentially affect how fast a technology can reach the flattening area, and what impact this might have on the prediction power of the model (Moore, 2015).

Hogan explained that non-linear models typically alter the resulting learning curve slope based on alterations to the theoretical first unit cost parameter *A*. However, the experience curve slopes of these models are not directly a function of the number of cumulative units produced. Contemporary models use a "step function" to reduce the learning rate to zero. Accordingly, the models amend the learning slope based indirectly on the number of cumulative units but only when interruptions to the production process starts to occur (Hogan, 2020).

Nonlinear experience curve provides an important managerial tool for long-term strategic planning. Once a technology reaches the flat end of the forecasting curve, the curve sends a message to managers that it is possibly time for change. A new curve is being created and a decision needs to be made on a certain technology to keep momentum. Figures 4.9 and 4.10 explains how the nonlinear curve provides information on the strategic inflection points at the end of each curve:

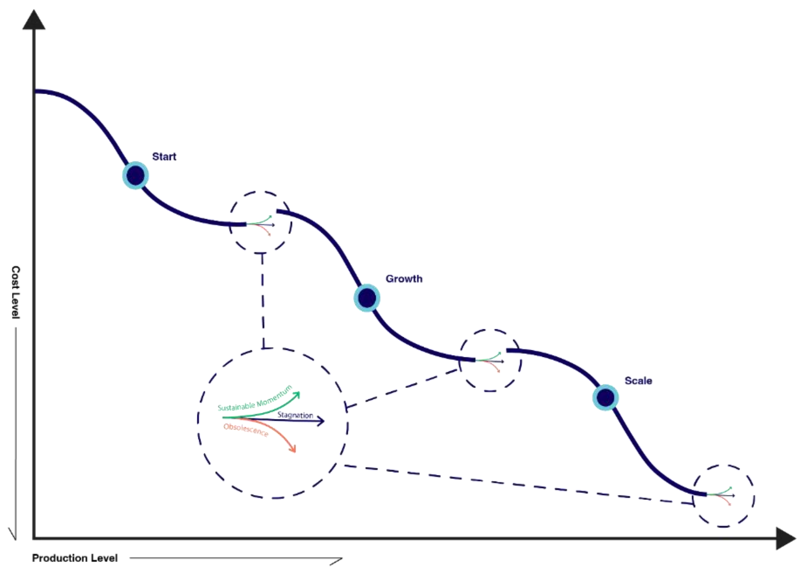

Figure 4.9: Technology strategic inflection points – Nonlinear experience curve

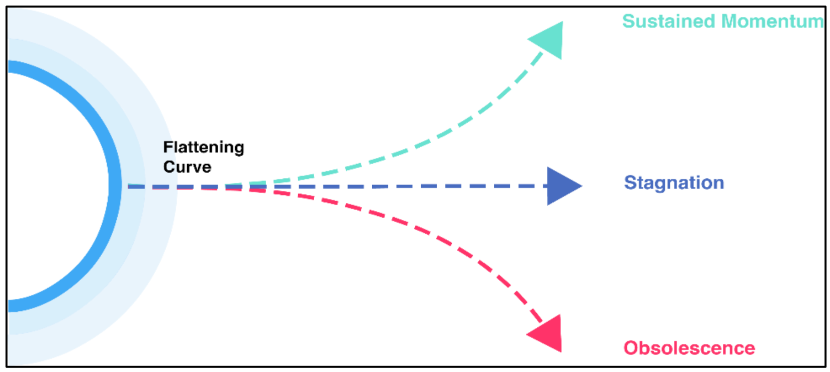

Figure 4.10: Flattening curve strategic inflection point options

4.7 Experience Curves Applications

The experience curve phenomenon, as labelled by the Boston Consulting Group (BCG), has had major impact upon corporate strategy, marketing strategy, and cost management. The experience effect often plays a substantial role in determining competition outcome in both local and international markets (Jarmin, 1994). The following section highlights the most important experience curve applications. It also provides evidence from literature on how useful they have been in reality:

Policy intervention:

Finding the sources of experience is important, yet finding the correct policies that support the experience curve implementation is very critical to unlock the full potential experience curves might provide (Dutton & Thomas, 1984). Dutton and Thomas (1984) wrote about "ill-defined task" when it comes to implementing policies regarding the experience curves (Dutton & Thomas, 1984).

In the policy intervention context, experience curves help in setting competitiveness policies, which aims at increasing the competitiveness of entrant technologies by increasing their installed capacity and assume that costs will decrease as accumulated production increases (Dutton & Thomas, 1984). Experience curves can lead in this case for the technology to be increasingly cost competitive in the marketplace and solve technology lock-in problem caused by mature technologies.

Furthermore, correct application of experience curves in policy formation helps defining early opportunities in market. It helps to illustrate the benefit of early investment and policy interventions in emerging technologies as well as the need for an initial market in order to allow emerging technologies to accelerate their cost reductions and reach cost competitiveness with existing technologies in the market earlier (Zhou & Gu, 2019).

To elaborate, experience curves are often used to extrapolate past cost (price) reductions to future cumulative production (or installation) levels to identify the additional investments needed for deployment of the entrant technology, while learning effects cover the gap between the costs of the entrant technology and the cost level of incumbent technologies (International Energy Agency, 2000).

Spence (2006) studied market entry and performance under a fairly wide variety of parameter specifications. He concluded that experience curves should be applied with caution as a policy intervention tool. Spence (2006) warned that experience curves can create substantial barriers to entry. He added that moderate rates of learning create the greatest entry barriers. “Where learning is rapid, new entrants may catch up quickly with the market leaders. For very low learning rates, only small cost advantages accrue to the early entrants” (Spence, 2006).

Strategic Management and cost competitiveness:

The use of experience curve in formulating corporate and firms’ strategy was early recognised in 1954 by Andress (1954), the Boston Consulting Group (1970), Arrow (1963), Dutton and Thomas (1984), Muth (1968), and others. Abernathy and Wayne (1974) reconfirmed the usefulness of experience curves for strategic planning in marketing, financial planning, and production. They described the experience curve as a strategy that “seeks the largest market share at earliest possible date.” (Abernathy and Wayne, 1974; Goddard, 1986). This, according to Abernathy and Wayne, doesn’t lead to gains in market penetration only; but also advantages over competitors who have not reached equal volume yet.

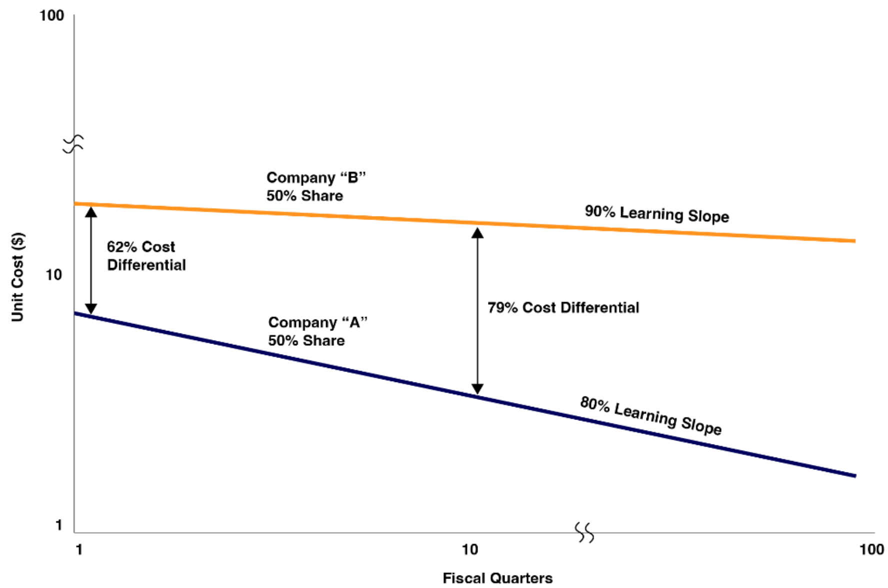

Figure 4.11: Cost competitiveness based on different learning slopes (Source: unknown)

The notion that unit costs and prices decline systematically in real terms as cumulative volume increases has been one of the most widely discussed and utilized concepts in the evolution of strategic management during the past two decades.

Strategy consultants early referred to several potential business effects of the experience curve. Business growth was always seen as a key strategic variable. "Based upon the experience effect relative costs should improve if a company were able to grow faster than competitors, thereby descending its experience curve at a faster rate," (Day and Montgomery, 1983).

Speaking on the experience curve, in Porter's (1980) famous presentation of generic business strategies, he identifies cost leadership as one of the three generic strategies. Experience based cost advantages represent one important way to achieve a cost leadership position.

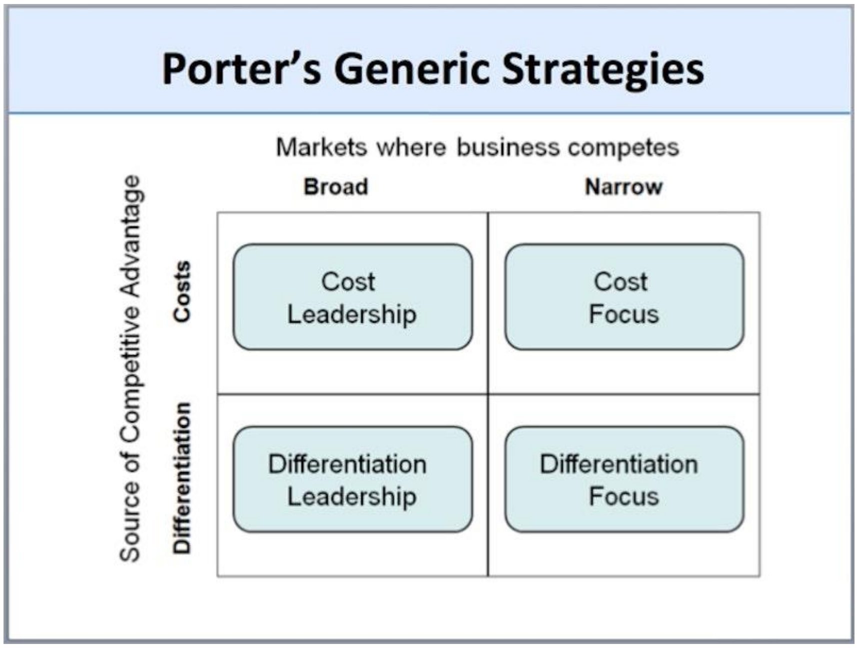

Figure 4.12: Porter's generic competitive strategies (Source: tutor2u.net)

To investigate this, Hall (1980) analysed sixty—four companies in eight industries subject to adverse environments, which lent credence to the Porter generic strategies. They achieved these results by establishing and maintaining a leadership position in terms of relative delivered product cost or relative product differentiation. A couple of companies were able to achieve leadership positions in both, but most found it necessary to achieve pre-eminence in one or the other (Hall and Howell, 1980; Day and Montgomery, 1983).

Two years later, Dutton and Thomas (1982) criticised using experience curves to achieve cost leadership in the market. They argued that acting on this belief - that the accumulating volume of a firm guarantees cost leadership – could leave the firm simply vulnerable to competitors achieving steeper learning slope and, accordingly, lower costs at the same – or even less – cumulative volume.

Hedley (1976) had earlier commented on the dilemma of the risk of misjudging while using the experience curve as a strategic planning tool (Hedley, 1974). Hedley emphasised an interesting point which is that the great potential experience curves have in strategic planning is restricted by the shortcomings and risks these curves suffer from. This risk, according to Hedley, is related to the continuation of a strategy applied based on the experience curve, and how it affects the production innovation and cost efficiency.

To eliminate this risk, Bodde (1976) suggested to use experience curves in long-term strategic planning, especially in the formulation of competitive strategy, more than in short-term business plans. In fact, Bodde warned of using experience curves to control day-to-day or short-term decision-making process.

Product Pricing:

Pricing a new product is a difficult task in industries where it is common to see rapid technological changes (Hossain, 2010). Experience curves provided an exceptional tool that can rationalise early investments and pricing of a technology that is presently uneconomical. For some time, there was a lack of research focusing on products and their pricing implications using experience curves (Hossain, 2010).

“The experience curve has increasingly become an important element in the formulation of many marketing models” (Day and Montgomery, 1983). This has been especially relevant for dynamic pricing models and models of new product diffusion. Effectively all these models utilise the conventional Equation 4.1 form of the experience curve.

The potential of these technologies can be graphically presented as an experience curve. The success of the investment decision made is conditional if a technology can "move down the experience curve," of being competitive in the future (Nordhaus, 2009). However, the steepness of cost decline is commonly linked to creative managerial efforts, not cumulative volume only (Dutton and Thomas, 1984). It is also important to keep in mind that the relative performance of penetration versus skimming pricing strategies depends on the interaction between cost and demand dynamics. In fact, Ericksons (1982) study found that the optimal price path was mainly impacted by market price sensitivity and competitive market entry rather than the presence of experience effects for the case he studied (Erickson, 1982).

That been said, using experience curves in product pricing for a portfolio of projects can be dangerous if the learning parameters and/or models are incorrectly calculated. Suppose, for example, that the true learning parameter is 0.1 and because of the biased discussed above the estimated parameter is 0.3. With a 3 percent discount rate and a 10 percent growth rate, the learning discount is overestimated by a factor of two.

4.8 Econometric Issues and Other Limitations:

The experience curve term has been frequently questioned in literature for so long. Day and Montgomery (1983), Nordhaus (2009) and Wene (2015) argued that present efforts related to the learning phenomenon from the economic perspective suffer from a major fallacy. Sahal (1979) asked various question on the experience curve definitions and whether they specify the type of improvements included. Is it improvements in technologies? The learning and experience of people to do the same job better? Changes in the nature and the design of the product? “Not all of these cases have “technology” as the main focus of the analysis,” said Sahal (1979).

The application of experience curves has been criticised (see for example Neij, 2003; Nemet, 2006; Nordhaus, 2009; Holmes, 2010) due to the uncertainties associated to the lack and treatment of data, and the aggregated approach to innovation.

The use of experience curves in models to assess the dynamics of future technology yet bears a number of problems which could lead to an overestimation of the learning effect. Ultimately, the critique articulates the need of complementary tools when analysing emerging, converging, and disruptive technologies.

Kiechel (1981) reported that the strategic implications of the experience curve phenomenon have been the subject of growing controversy over the years (Kiechel, 1981; Day and Montgomery, 1983). The application of this phenomenon “presents a bewildering array of practical problems, whose solution is at best only partially understood,” said Day and Montgomery (1983). Among most reported economic considerations and limitations of experience curves applications are:

4.8.1 Reliability of the Learning Rate

The experience curve equation describes a highly dynamic process through mainly two correlated time series: input and output of the experience curves (Schilling & Esmundo, 2009; Candelise et al., 2013). Given the empirical nature of experience curves, the fact that the learning rate changes over time leads to methodological issues: a constant learning rate is typically one of the fundamental assumptions of the conventional experience curve methodology.

Learning rates are often uncritically assumed to remain constant in the future following conventional experience curve models as discussed earlier in the research. This assumption, however, has been criticised early in literature since the 1940s (Carr, 1946; Conway and Schultz, 1959). Day and Montgomery (1983), Alberth (2006), and Boone (2015) emphasise that it should not be taken for granted that past experience curves can always be extrapolated at the same constant rate.

Assuming that the relationship between experience and cost will remain constant in the future becomes even more problematic if the experience curve analysis does not provide details about the deeper cost drivers (McDonald & Schrattenholzer, 2001; Papineau, 2006; Schilling & Esmundo, 2009; Hansen et al., 2017). The critics argued that using constant learning rates leads to a false sense of certainty regarding the potential future cost reductions of individual technologies.

Moreover, the learning rates can vary significantly across the same data sets using different approaches (Henderson, 1984; Hogan, 2020). It is the factor that is most affected by changes and uncertainties which makes it more relevant to question the constant learning rate assumption as realised for years in literature.

Speaking of data, learning rates can also witness differences across various studies and industries. One major issue in using experience curves is how to correctly treat the historical data to calculate a learning rate (McDonald & Schrattenholzer, 2001, Hogan, 2020). Depending on the spread of the data, it is possible to manipulate the data to calculate different learning rates by changing the starting and ending point of the analysis and the choice of including or excluding outliers (Rubin et al., 2007; Nordhaus, 2014).

McDonald and Schrattenholzer (2001) found that performing these calculations for individual technology shows a distribution of learning rates within a single technology that is nearly as broad as that across technologies (McDonald and Schrattenholzer, 2001). Other technologies, according to Rubin et al., show learning rates becoming negative in early periods before increasing (Rubin et al., 2007). Furthermore, historical datasets for new technologies may be very short and thus impose greater uncertainty due to a small sample size.

Another criticism on the learning rate was reported as early as 1947 on the robustness of learning rate to model specifications. Crawford and Strauss (1947) examined learning rates from 34 industries assuming zero exogenous technological change; only 4 have estimated empirical learning coefficients in the plausible range between 0 and 0.5. The conclusion is that estimates of the learning coefficients were not robust to specifications. Moreover, the estimates were often well outside the theoretically acceptable range used in this study (Crawford and Strauss, 1947).

Alchian (1963) reported a great variation in the actual *b* values experienced in different airframe start-ups during World War II (Alchian, 1963). This criticism was confirmed by Bass (1978) who found great variability between the slopes of the experience curves for six consumer durables (Bass, 1978). However, researchers were reluctant, to cite his results as a refutation of a uniform slope across products, because of weaknesses in his methodology. First, he employed price data as a surrogate for cost, leading to obvious problems of identification. Secondly, Bass ran regressions on various time periods (e.g.: on monochrome televisions, separately for the periods 1948-1960 and 1948-1970). However, BCG data show a break in the price series in 1954 which supports Bass' methodology (BCG, 1970). Variation in learning rates due to different data periods can be explained by the nature of the technological innovation. Technological change process, from innovation to market maturity, takes considerable time, generally decades. Therefore, the longer the technology is under development and deployment in the market, the more records of data depicting its progress are available.

McDonald & Schrattenholzer (2001) lead the most recent comprehensive review on the variability in learning rates in energy technologies in which they confirmed earlier observations on this matter (McDonald & Schrattenholzer, 2001). Their study became a reference study on this specific issue, learning rates variations, for many years.

That been said, stable learning rate estimates can be achieved. However, the situation can be different for emerging technologies, whose market price data is often influenced by the overrepresentation of external factors (e.g., market power) and short-term development characteristics (e.g., cost overruns, unit upscaling) (Elsharafa, 2018). Therefore, it is vital to recognise whether the experience model omits the influences of specific learning mechanisms or factors by excluding observations from the dataset (Alberth, 2006; Takahashi, 2013). Should those factors be inherent to the development process, the learning rate estimates would be biased.

Among suggestions made by Schilling (2009) to tackle this challenge is to perform several models runs when modelling the future costs of individual technologies, using ranges of plausible future learning rate values in order to reflect the associated uncertainties (Schilling & Esmundo, 2009), or, of course, try different functional form to model the experience curve that implies non-constant learning rate.

To conclude, care must be taken to treat the data in a way that produces a representative learning rate (McDonald & Schrattenholzer, 2001; Papineau, 2006). The concept of different cost development phases was developed and discussed to help understanding the issue of how to use experience curves when there are dramatic changes in the technology itself, such as breakthroughs[31], or in a technology's market circumstances, such as the appearance of a competing technology (Nemet, 2006; Rubin et al., 2007). Any of these variations could affect the calculation of the proper learning rate from the historical data. However, breakthroughs may not be captured by the learning rate, leading to a separate introduction of them through varying exogenous assumptions (McDonald & Schrattenholzer, 2001).

Schoots et al., (2010) claimed that unless economies of scale effect are separated from learning, of internal feedback between various ways of learning and technological and national spillover effects, there is a risk that learning rates are mostly overestimated. The solution Schoots et al. (2010) suggested is to separate the effects of learning from other factors to the extent possible (Schoots et al.; 2010). At the least, factors such as commodity prices would be removed by correcting observed data with a commodity price index at the least (van der Zwaan et al., 2011).

Furthermore economies-of-scale should be excluded too as these are based on a different cost reduction mechanism and render data from different manufacturers incomparable (Schoots et al., 2010). The issue with these suggestions is that neither Schoots et al., nor others provided a solid practical approach on how to do so.

[31] Which could lead to under or over-estimations of technology future costs.

4.8.2 Omitted Variable Bias

Omitted variable bias is a major issue for experience curves, and can be reduced by the addition of explanatory variables as it may distort results (de La Tour et al., 2013). If the omitted variable bias prevents from accurately measuring the effect of each variable, the consequence on the accuracy of the predictions is not straightforward (Alberth, 2006). To evaluate this, many studies were conducted to examine models results without and with additional variables and compare them. Rapping (1965) found that omitting raw material prices would tend to bias downward the estimates of capital and labour elasticities. Lieberman (1981) found that the price experience slope rose from 71% to 77% when scale, new plants, and entry were incorporated into the model (Nemet, 2006).

4.8.3 Data Limitations

The limited availability of consistent datasets means that elevated uncertainties are associated with the estimation of experience curve models. Uncertainty in historic cost data is repeatedly reported in literature as a challenge for experience curve estimates. Insufficient empirical data can lead to substantive learning rate uncertainty (Alchian, 1963; Henderson, 1984; Grafström & Poudineh, 2021; Way et al., 2022).

As mentioned before, and for reasons of data availability, market prices are frequently used as a proxy for market costs being the dependent variable during the construction of experience curves. This applies to many types of datasets needed to estimate the experience effect. For example, data on R&D investment is scarce, in particular when a high level of technological disaggregation or private sector investment is needed. Data on corporate R&D expenditure are even more difficult to obtain, especially when focusing on the R&D expenditure by technology (Jacquier-Roux and Bourgeois, 2002; De Nigris et al., 2008; van Beeck et al., 2009). Even if data were available, attention needs to be paid to the fact that companies may over- or underestimate them for strategic purposes as mentioned in section 4.7 (Jacquier-Roux and Bourgeois, 2002; Gioria, 2007).

The R&D data scarcity can be explained by a combination of various factors. No regulation obliges private companies to report their R&D investments, unless they are listed on the stock-markets and thus need to also present their financial accounting and an annual report[32].

This also makes it difficult to calibrate reliable learning by searching rates. To remedy this, the use of patents, as previously suggested, may be one option. However, this solution has its problems too as manufacturers may choose their own policies which may limit some companies' propensity to patent.

On the other hand, Henderson (1984) stated that, in competitive markets, there is a very close correlation between costs and prices that can be assumed. What makes this assumption valid, according to Elshurafa (2018), is the fact that if a company charges prices considerably higher than its costs, it will not remain competitive (Elshurafa, 2018).

However, critics point out that this is not necessarily the case in real world markets. It happens that individual technology suppliers may exert market power over prolonged periods of time, a situation that allows them to charge considerable mark-ups (Day and Montgomery, 1983; Henderson, 1984). If the mark-up between costs and market price is assumed to be constant while, in reality, it varies considerably over time, wrong conclusions about the actual experience curve and its associated learning rate are likely to be made (Abdou & Mahmoud, 1977; Henderson, 1984; McDonald & Schrattenholzer, 2001; Jamasb & Köhler, 2006).

Despite the concerns, reliable historic cost, and sometimes price data, is often difficult to source. In the early years of a technology's deployment, data is often scarcer and more uncertain. In early years, markets are small, and the prices charged in niche markets by only a few market actors are not always publicised. Kohler (2006) explained that the risk of uncertainty about early costs or prices can be a problem for

[32] There is no clear methodology in the Multi Factor Experience Curve (MFEC) literature that standardises the impact of public R&D in relation to learning rates where both R&D and learning by doing effects are included.

experience curves as early data points can have a significant influence on the slope of the experience curve and, consequently, its learning rate (Kohler et al., 2006).

Researchers tried to address this criticism on the empirical data by discussing to what extent prices and costs might deviate during the observed time period and – if possible – correct observed prices for market power (BCG, 1968; Henderson, 1984; Hansen, 2017; Grafström & Poudineh, 2021) . Also, efforts have been made to build reliable historic cost or price databases, by carefully analysing existing datasets and refraining from using data that appears to be unreliable for research and analysis purposes.

4.9 Experience Curves for Solar PV Technologies

4.9.1 Solar PV Market Growth

Operating in competitive markets makes individuals and industries do better. This fact is at the heart of the experience curve phenomenon which is one of the biggest stories in solar power industry. Hence, the focus of this thesis is to analyse how learning through market experience reduces prices for energy technologies and how these curves were used to set targets to make new energy technologies commercial.

The first price outlook of historic PV modules dates back to the 1950s, when the cost of PV energy was 256$/W in 1956 (Hass et al., 2022). According to Hass (2022), this would be around $2500 today when adjusted for inflation. During this era, solar PV energy was mostly used in aerospace before it entered other applications around the 1970 (Kavlak et al., 2018). Accordingly, the cost of solar PV modules started to drop rapidly with sparked interest in the effect of technological learning on PV systems (Nemet, 2006; Haas et al., 2022).

The growth in this industry was also driven by the growing concern for global warming following the increased CO_2 concentration in the atmosphere and the need for a fast transition to clean energy sources (Parente et al., 2002; Farmer et al., 2016; Hansen et al., 2017). This concern is reflected in the agreement at the 2022 United Nation Climate Change Conference, COP 27, stating that a cut of greenhouse gas emission by 25-30% is necessary by 2030 (Source: IMF report, 2022). Therefore, it is crucial to have reliable estimation and forecasting of renewable energy technology costs, for the purpose of reducing the uncertainty surrounding policy decisions to help increase clean energy generation (IEA, 2000; Papineau, 2006).

The success of the renewable energy industry's expansion can be measured both by the level of cost reduction and the extent of market penetration of renewable technologies (Papineau, 2006). The two are linked as the price decline both causes, and is caused by, the increasing number of solar installations.

In regard to the solar power industry, it is one of the fastest growing renewable energies in the renewable energy market. The applications for solar energy are enormous such as: electricity generation, transportation, photochemical, solar propulsion, solar desalination, and room temperate control. With more developments in the market, solar energy and its transfer to electricity energy will have the potential for wider application and deep impact on our society, so it has attracted the attention of the researchers (Y. Chu, 2011).

Besides the passage of time, these developments need to be accompanied by government support through funding Research and Development (R&D) and through price subsidies (IEA, 2000). Over the years, Research and Development (R&D) investments contributed to the improved module efficiency and gained technological learning in solar PV modules manufacturing (Kavlak et al., 2018).

The observed learning rate between 1979 and 2012 for solar PV modules was 22%, as calculated by IRENA (IRENA, 2021; Haas et al., 2022). Since 2000, the global production of solar photovoltaic (PV) modules has grown with a CAGR[33] of over 40% (Jäger-Waldau, 2018), but installations varied significantly at the country level. The rapid increase of the annual production in China since 2006 has created a new global trend in the solar PV growth. Accordingly, Annual new solar PV system installation increased from 29.5 GW in 2012 to 168 GW in 2021. Within few years, world-wide PV power has quadrupled to more than 940 GW at the end of 2022 (Statista, 2023). Figure 4.12 provides a glimpse on the global level of the global cumulative global installed capacity between 2000 and 2021:

[33] Compound annual growth rate.

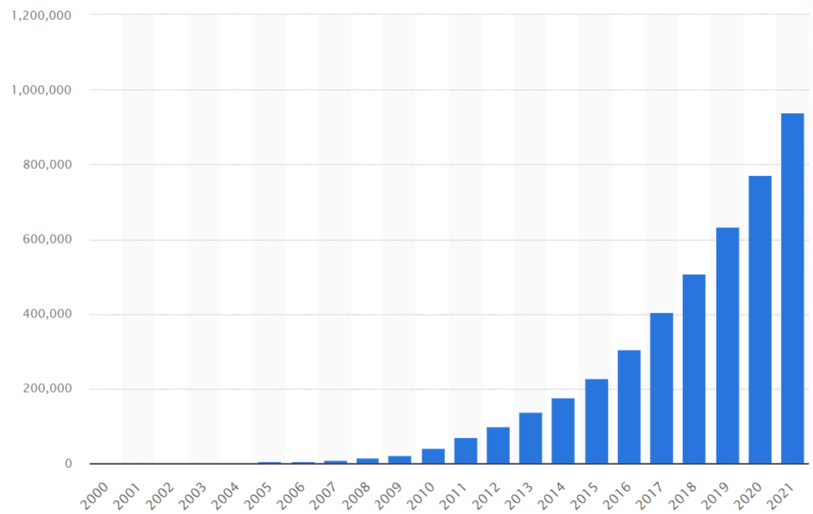

Figure 4.13: Cumulative installed solar PV capacity worldwide in MW from 2000 to 2021 (Source: Statista)

Developments in solar PV modules production and installations were accompanied by a dramatic fall in the cost of producing solar PV energy (Nemet, 2006; Nagy et al., 2013; Kavlak et al., 2018; Lafond et al., 2018). It is now the cheapest way to produce electricity in many parts of the world, even in cloudier and cooler parts such as the UK. The cost of solar is now reaching "grid parity", at which the cost of solar is the same as the average cost of the overall basket of energy sources for the electricity grid as a whole (Dutta & Das, 2020). With more than 40 years of growth, solar PV energy provide a clear example on how the development of the experience curve in these emerging technologies[34].

[34] Selling prices of modules are used as the benchmark for cost in the PV industry for many reasons. Modules can essentially be treated as a commodity; several organisations track and publish the spot price of modules. As such, monitoring the module price evolution gives a global picture on how the industry is progressing (IEA, 2020). However, solar PV demand is driven by policy changes and incentive policy, which might affect the price irrespective of cost. Söderholm and Sundqvist (2007) warned that, for models that depend on historical data, that might cause a major concern. Söderholm and Sundqvist said that it is a bad practice "to use an estimated econometric model found suitable for one time period when attempting to predict what will happen in another period under a different set of policy rules, for example with different feed-in tariffs for some major countries." (Söderholm and Sundqvist, 2007)

4.9.2 Solar PV Technologies

There are different types of solar technologies that are currently available in the market. However, each of them is based on quite different concepts and science and each has its unique advantages (Y. Chu, 2011). Nowadays, the major direction of growth in solar technology development is linked to Photovoltaic systems. Photovoltaic (PV) technologies, also commonly known as “solar cells”, directly convert the solar energy into electrical energy (de La Tour et al., 2013; Elshurafa et al., 2018). “A PV module is an array of packaged solar cells that convert solar energy directly into direct-current (DC) electricity” (Harmon, 2000).

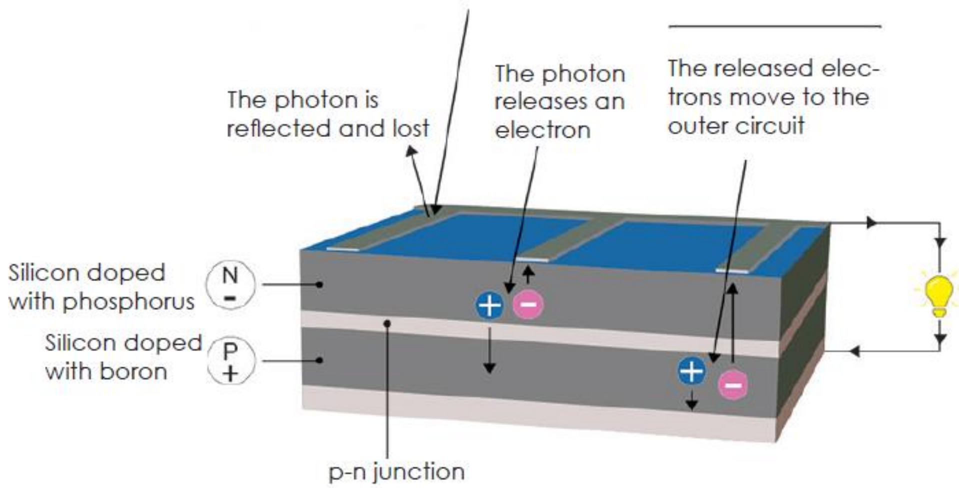

Figure 4.14: How a Photovoltaic (PV) cell works (Source: planete-energies.com)

“Silicon is the most common semiconducting material in use in PV modules due to its abundance” (Harmon, 2000). Over 90% of solar PV cells market is composed by silicon-based cells, therefore, the decreasing cost of silicon is critical for the growth of solar PV sector (Muraleedharakurup et al., 2016). Silicon is the main component for the development of solar cells, it also has to be processed to attain the required purity for solar PV appliances, usually starting from metallurgical-grade silicon. Table 4.1 summarises the main elements of a solar PV system and their functions:

System	System Element	Function
Solar PV system	Solar cell	Absorption of solar irradiation and conversion into electric current through *photovoltaic effect*
	Solar Module	Connection of 'string' of cells to achieve desired output voltage; protection of cell from moisture and structural damage; insulation of electrical current
	Mounting System	Integration of modules into larger structures (array); load carrying and transfer (mounting system); integration of module / cells into building environment (building integration); reorientation of modules / array to follow the sun (tracking system)
	Grid Connection	Conversion of DC current into AC (inverter); reduction of impact of grid-side disturbances; maintenance of grid-friendly system output (electrical control svstem)

Table 4.1: Elements of solar PV systems

PV systems consist of two major subsystems of hardware: PV modules and the Balance-of-System (BOS). The basic element of photovoltaic technology is the solar panel, while all other parts which contribute to the functioning comprise the "Balance of System" usually denoted by the acronym (BOS). Technology costs for solar PV technologies include module cost, inverter costs, balance of system (BOS), installations, and other indirect costs (Ioannis, 2017).

Generally, cost of production will fall faster for highly standardised, repeatable, modular products. It will fall slower where there is a greater degree of variability, customisation, regional differences or batch processing in the design. The price will follow the cost of production unless supply & demand imbalances, consumer choice or marketing ploys intervene (Candelise et al., 2013; Elshurafa et al., 2018).

Solar PV systems are further differentiated based on the size of the photovoltaic sub technologies as follows (Ioannis, 2017):

1. Utility-scale with one-axis tracking, >10 MW
2. Utility-scale without tracking, >10 MW
3. Commercial-scale on flat surface, 20 kW - 2 MW
4. Residential-scale on inclined surface, <20 kW

As for the scope of this research, silicon-based solar PV modules cumulative installed capacity and cost data are analysed. The reasons are because they represent more than 90% of the solar PV market, they are likely to stay around for longer, and cumulative data (from all systems sizes) are found in well-established databases which allow a meaningful analysis.

4.9.3 Experience Curves and the Effectiveness of Solar PV Energy Production

Since 1990s, experience curves have moved from obscurity to mainstream within energy technology policy. Scientists and analysts from academia, industry, and government agencies who were mainly participating in a workshop arranged by the International Energy Agency (IEA) in 1999, observed that experience curves "are underexploited for public policy analysis" (IEA/OECD 2000; Muraleedharakurup et al., 2016; Samadi, 2018). They therefore recommended that experience curves "are used to analyse the cost and benefits of programs to promote environment friendly technologies" and "are explicitly considered in exploring scenarios to reduce CO_2 emissions and calculating the cost of reaching emissions targets" (IEA/OECD, 2000). The IEA Committee on Energy Research and Technology (CERT) showed support to the findings of the workshop and launched an international collaboration. McDonald and Schrattenholzer (2001) provided the first overview of experience curves for energy technology.

Since then, major high-level policy documents embrace the insight from experience curves into the crucial role of market deployment. Given the increasing interest in how a rapid reduction in the cost of solar energy could be, experience curves have been extensively used in the academic literature to explain the historically observed cost reductions in solar PV modules and predict future pathways (Nordhaus, 2014).

However, there are also indications of fading momentum and expectations on the curves as efficient and legitimate tools for scenario analysis and policy making. Solar PV technologies have been analysed as a key example to justify the relationship between a technology's cost reductions and cumulative installed capacity (Nemet, 2006; Swanson, 2006; Candelise et al., 2013; de La Tour et al., 2013; Dutta & Das, 2020). Despite the strong empirical evidence on the existence of technological learning in solar PV technologies, Söderholm and Sundqvist (2007) identified several econometric issues concerning experience curves. For example, Söderholm and Sundqvist (2007) highlighted that the learning rate can differ across time for the same technology; as a new technology can experience a wave of new innovations at the beginning, but after many years the easy opportunities for cost reductions may be exhausted (Söderholm and Sundqvist, 2007; Grafström & Poudineh, 2021). However, there was no critical assessment on the specifications of the models that could tackle this issue, to our knowledge.

There are several weak links in the technology-energy-climate chain studies. The status of technology learning and uncertainties in extrapolated experience curves and the difficulties in implementing general measures globally have already been mentioned. Technologies to increase energy efficiency interact with many factors internally and externally which makes it problematic to analyse them separately.

The importance of addressing these issues stems from the inherited limitations that the solar PV industry suffers from despite the impressive growth. Companies operating in this sector are currently faced with problems related to the most effective way of solar energy production. Among these limitations are:

1. Physical space limitations: one of the most reported challenges in the solar PV industry is related to limited space to build solar PV systems (Grafström & Poudineh, 2021). This challenge is more relevant when companies need significant areas of land which are scarce in infrastructure-packed city centres for example. Here comes the importance of innovative technological solutions to tackle this challenge with more advanced transparent PV glass for example, which represents an alternative to the space limitation (Nemet, 2006; Papineau, 2006; Hansen, 2018; Haas, 2022).
2. Enough access to sunlight: the amount of the solar energy received on earth everyday varies depending on weather conditions, geographies, and the type of solar setup (Ioannis, 2017, Haas, 2022). The impact of this limitation manly depends on the size of the solar PV installation. For example, in smaller-scale solar PV installations, one may argue that sunny weather is needed to reap the most solar power, while for efficient large utility-scale solar power plants, companies look to high-sunlight desert or semi-desert areas to build large solar power plants. Finally, when it comes to the type of solar system used, there are also solar power plants tracking the sun's position for the best solar energy capability (Elshurafa et al., 2018).
3. Solar's intermittency (aka. Storage challenge): the mismatch between the peak generation and peak demand is a serious challenge for growth in the solar PV industry (Koskinen, 2016; Hansen et al., 2017; Lafond et al., 2018). The timing of the sunrise in the morning and sunset in the evening, with peak solar power generation in the afternoon does not correspond with the highest demand for it (which is when the sun sets). Solar technologies would supply power in excess of customer demand in the middle of the day, which demands highly efficient ways of storing excessive solar energy for peak demand times to cater to needs at any time. (Schilling & Esmundo, 2009; Rypdal, 2018). "Given that solar energy is an intermittent source, it is much easier for it to contribute when it supplies only a minority of energy: new supporting technologies will be required once it becomes a major player" said Lafond et. al (Lafond et al., 2018).

4. Technology lock-in: economies of scale (EOS) have been known to serve as a barrier to entry for new competitors in the solar PV modules market (Grafström & Poudineh, 2021). Most solar PV modules producers are focusing on aggressive cost-cutting, from the upstream production of polysilicon to the downstream deployment of silicon panel-based installations (Nemet, 2009; Koskinen, 2016). This tendency puts the industry at risk of technology lock-in, entrenching the dominance of silicon solar PV. Economic theories of lock-in suggest that an incumbent dominant technology has the advantage over emerging technology upstarts (Nemet, 2006). Even if upstarts hold the potential to cost less and perform better, they might flounder in a free market that favours first movers.

   By 2030, the cost of electricity from silicon solar PV projects could halve, making silicon an even more formidable incumbent (Harmon & Schrattenholzer, 2000; Yeh & Rubin, 2012). Even far superior and cheaper technologies might face challenges by slightly incrementally better silicon panels (Papineau, 2006). There is no way to tell whether the lock-in might be happening right now. Silicon may fall rapidly in cost than currently anticipated. The fall in silicon solar panel prices is beneficial in the short term, but the drop makes it harder for emerging technologies. In this case, emerging technologies might not be cost competitive before economies of scale kick in at mass production to compete in the market in the long run (Haas, 2022).
5. Law-related and political context: over the years, the actual growth of solar energy implementation has been depending heavily on governmental incentives for such projects and these vary from country to country. The actual business activities of solar industry entities are largely defined by country-specific tax exemptions, energy policies and laws, and state-regulated promotion activities for the solar energy sector (Feldman, 2016; Hansen, 2018). Despite the benefits of these incentives, the solar PV industry needs to be independent and competitive with and/or without the incentives to be able to participate as a game changer in the global energy market.

6. Solar waste and environmental concerns: As for solar PV panels, there are other safety concerns laying in health hazards and pollution risk. Compounds such as: lithium, silicon tetrachloride, cadmium telluride, and copper indium selenide, used to manufacture solar energy assets, are potential environmental pollutants, in addition to their toxicity for human health. For example, lithium (used among others in solar batteries) can pollute tap water and irrigation water in areas where lithium batteries are not utilized (Y. Chu, 2011). Effective utilization of solar waste is also a challenge. The global volume of solar-panel waste generated annually is expected to rise from 30,000 metric tons in 2021 to more than 1 million tons in 2035. To avoid posing danger to ecosystems and communities, it's crucial that solar energy industry companies handle these concerns according to regulations as well as circular economy best practices (Haas, 2022).

Innovative solutions are recommended to tackle some of the above-mentioned challenges in the PV sector. Among solar photovoltaic innovations that are driving the development of the solar PV industry are: Thin-film photovoltaic technology (mostly cadmium telluride (CdTe) and copper indium gallium diselenide (CIGS) solar cells), Perovskite photovoltaics, solar glass, floating photovoltaics (PV on water), bifacial photovoltaics, recycling and reusing outdated solar panels.

Moreover, companies need to find their niche and competitive advantage to be able to compete at the end customer experience level, and launch successful solar products and services supported by software solutions. These solutions include performant software that enables users to reap the most benefit, regardless of their level of expertise. Examples on innovative software in solar PV industry include household energy management software supported by energy management software's functional goals, Solar tracking system tilt automation, Photovoltaic system remote monitoring, and addressing solar systems technical issues.

4.10 Conclusion

This chapter provided more details on the empirical construction of the experience curves and the factors that affect this phenomenon. It also discussed the nature of the analysed costs used in technology forecasting.

This highlights one of the concerns in experience curves literature on the factors that cause the experience effect to occur. The chapter yet discussed the number of variables used in the model to estimate technology cost, explaining the advantages and disadvantages of each approach.

Considering the most reported econometric limitations, the chapter provided details on the non-linear experience curves used in this research; which are important for the reader before moving to the methodology and perform the statistical analysis using these models.

It is important to move to second part of the study with a clear idea on the whole big picture. Accordingly, the chapter concluded with an introduction to the solar PV technologies and the challenges facing this industry which will likely affect the learning rates. Whether constant learning rate, via linear experience curve model, is appropriate or not for solar PV technology cost forecasting, is what the next chapters will try to address.

To our knowledge, and after this extensive review, testing the flattening effect in solar PV modules experience curves against conventional linear models has not yet done, which gives us the opportunity to fill this critical gap in literature on technology cost forecasting. This will help derive plausible future ranges for technological learning rates for several emerging technologies.

Chapter Five: Methodology

5.1 Chapter Overview

The purpose of the methodology chapter is to fully explain the methods back of the research question that contemporary experience curve models may provide better accuracy than conventional models when estimating technology production costs using capacity/production data. As explained earlier in Chapter Four, technological learning fluctuates and does not remain constant over time. Hansen (2017) and Hogan et al. (2020) state that the conventional method lacks the application of the diminishing learning rates (the non-constant learning rates). The non-linear models chosen for this analysis encompass the diminishing learning rate behaviour and the flattening effect at the end of the curve, in both symmetric and asymmetric convergence. By considering these factors, contemporary experience curve models may provide more accurate forecasting tool for technological cost.

Finding methods to increase the accuracy of the experience curves estimates are of great value. It helps estimators by increased accuracy that leads to less forecast error. Therefore, the basic method of this research is to *statistically test* which experience curve model is the best predictor of cost. Using the same dataset, non-linear experience curve models (Gompertz and the Logistic models) are compared to the conventional linear model (Wright's model) to determine which model's type is more accurate.

In this respect, Chapter Five clarifies, in depth, the application of the models, methods for comparison, and data analysis. Regression analysis is often used in literature to estimate experience curve models coefficients, and yet it is used in this analysis. Each of the predicted solar PV module costs for the alternative models will then be compared to Wright's model and to the actual modules costs to calculate the error. The goal is to manifest how and why the methods used were appropriate to answer the research questions, and test the hypotheses, presented earlier in Chapter One, based on various measures of significance.

5.2 Research Approach and Design

In line with the positivist research philosophy explained in Chapter One, the research approach adopted for this study is a quantitative and deductive analysis that aims to test an established theory on experience curves and build onto it with collected data. This means that the research is explanatory and aims to achieve "depth" rather than breadth, based on objective findings. A deductively based analytical approach allows for results to emerge from the data as it is being collected in order to test hypotheses and relationships (Bryman and Bell, 2011; Saunders et al., 2012). Deductive research implies generating and formulating specific hypotheses by the researcher about a phenomenon based on existing practical and theoretical knowledge (Head, 2008). As mentioned earlier in Chapter One, the hypothesis is then tested under scientific experimental conditions explained in steps in this chapter. The result of such an analysis is the confirmation or rejection of a hypothesis. Should the data support the hypotheses, then the hypotheses hold. If not, that means the theory underlying the hypothesis is challenged or, at least, it has reached its limits (Boone, 2018).

Quantitative research is the common approach within the positivist research philosophy. It is a common practice in the social sciences to test specific theoretically motivated research hypotheses using formal statistical procedures. This approach, however, assumes that the research was well designed and carried out rigorously (Hyndman and Athanasopoulos, 2018) to avoid misleading results. Accordingly, it is important to select the most appropriate method to ensure the validity and accuracy of data and findings.

The research design decision requires a thorough understanding of the purpose of the research, which is explained in detail in Chapter One, and frequently highlighted over the chapters. The strategy implies an epistemological approach of having an experimental case study, that allows the researcher to test the hypotheses and understand the relationships between the analysed variables. The examined timeframe involves studying a sample over a longitudinal timeframe to understand the behaviour of the proposed experience curve functional forms. On the next page, Figure 5.1 summarises the flow of the methodology applied in this research as way of background:

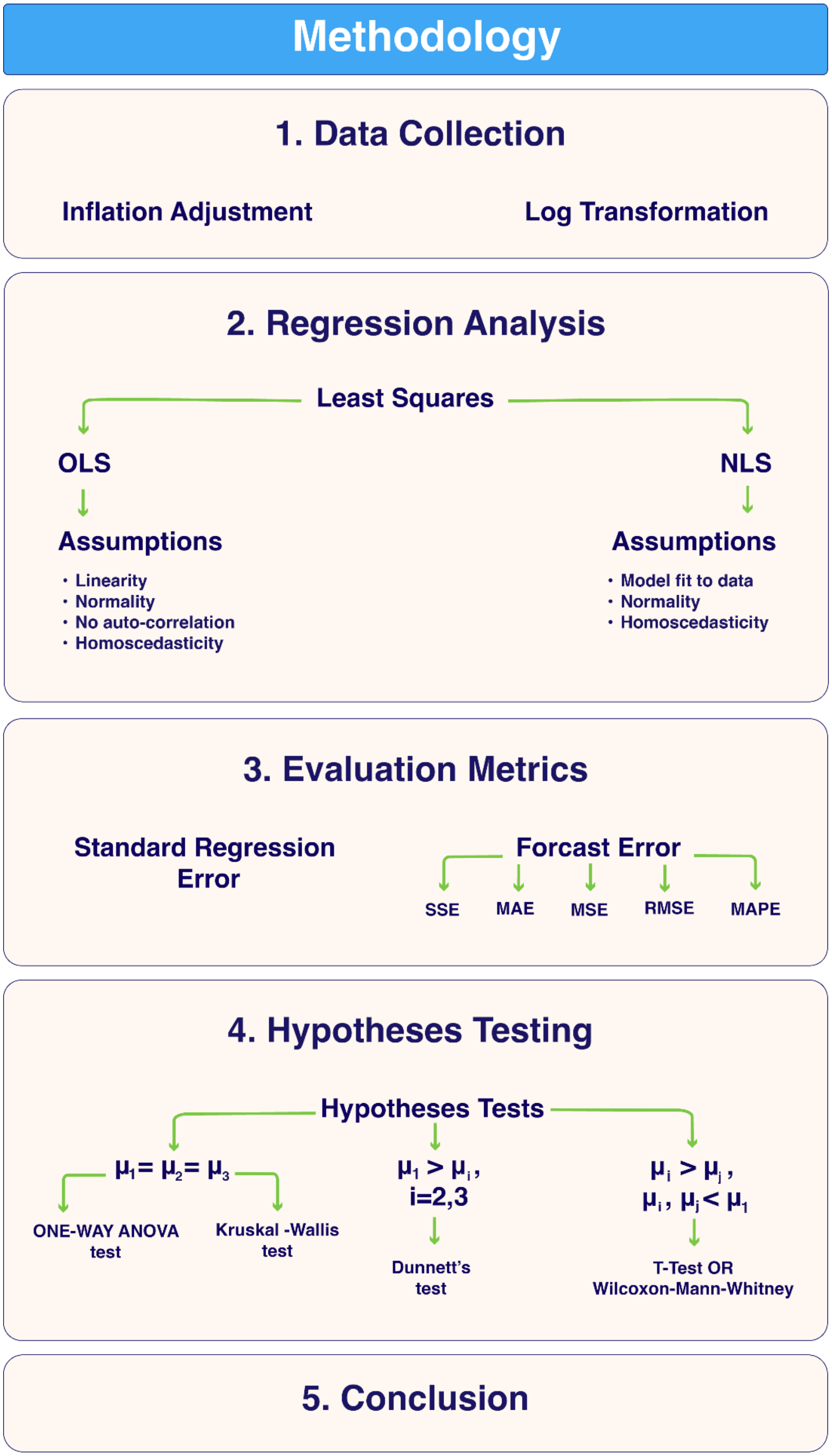

Figure 5.1: The research methodology flow

5.3 Data Collection and Analysis

5.3.1 Data Collection

The next step in the research process is collecting the data needed to complete a meaningful statistical comparison to decide on the best fit model (Moore, 2012). The data collection method (or methods) depends on the type of data the researcher plans to collect (Badiru, 2012). These two are tightly linked to the research philosophical approach outlined earlier in this chapter.

As for the scope of this research, a *secondary time series* dataset is used to perform the statistical comparison between the selected models. For time series datasets, anything that is observed sequentially over time is considered a time series. Forecasting time series data typically implies estimating how the sequence of observations will continue into the future (Hyndman and Athanasopoulos, 2018). Examples of time series data include daily IBM stock prices, monthly rainfall, annual Google profits, etc.

Data used in this analysis was pulled from many sources, mostly free and openly available on the internet, but occasionally via standard university-wide subscription licenses held by the University of Brighton. *Production and capacity data* come mostly from the International Energy Agency (IEA), *Our World in Data* databases, Bloomberg New Energy Finance (BNEF) and Bloomberg L.P. (via Bloomberg Terminal), and BP's Statistical Review of World Energy. More details on data sources can be found in Appendix 1.

Accurate *price data* is harder to find and comes from a wide variety of sources including, among others, Bloomberg New Energy Finance (BNEF) and Bloomberg L.P. (via Bloomberg Terminal).

The main challenges while using these sources were: First, most databases are paid and not freely accessible for researchers to use. Experience shows that it is not always possible for researchers to pay for expensive data sources. For the purpose of this research, University of Brighton granted students access to Bloomberg Terminals for data collection purposes, which helped in this research study. As for other sources, only free databases were used where available.

Second, the size of data available on innovative and emerging technologies in general. It is typically optimal to have large samples to ensure robust and reliable results. However, with emerging and new technologies studies, the size of the available dataset is likely to be limited. Although it adds to the modelling challenges especially with complex models (e.g.: non-linear models), it is part of the whole generation of knowledge that researchers need to deal with. This limitation applies to the sample size collected for the sake of this research as the Solar PV energy has first started in the 1970s with very low installation levels and high prices – an issue that will be discussed in more detail in section 5.3.2 of this chapter.

Global cumulative installed capacity of solar PV power is gathered from plant-level cumulative installed capacity at the global scale. Plant-level cumulative installed capacity represents the stock of installed capacity of solar PV modules of particular plants. It is the main variable chosen in this research which to act as a surrogate for experience and changes in performance in the solar PV industry at the global level[35]. Our dataset consists of cumulative installed *silicon-based solar PV modules* capacity at the global level measured in *Megawatts (MW)*. This choice is based on PV modules specifications discussed in Chapter Four.

To summarise, only module types with at least twenty years of performance data appear to be a useful option for the analysis, which mainly applies to silicon-based solar PV modules. "It is important to have data span several years for comparison purposes. The historical data is important because the effects of learning are evident. Having data spread over a period of time shows patterns." (Johnson, 2016)

In parallel, only silicon-based modules prices were also used for this analysis for a number of reasons. First, using silicon-based modules prices allows for the assumption of homogeneity over multiple module types.

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[35] In his famous paper, *"Debunking the learning curve*," Goddard (1982) argued that annual installed capacity has advantage over cumulative installed capacity by reflecting the annual changes in the industry (Goddard, 1982). Using annual installed capacity is an approach used in literature. However, cumulative installed capacity remained largely used for years and it gave robust results (Goddard, 1982). The choice depends on the purpose of the study, and which aspect of the experience curve models is being analysed.

It makes it possible to compare the prices and continue the assumption of learning over the years. Second, silicon-based solar PV modules are expected to dominate the market for a long time due to economies of scale, technology lock-in effect and other reasons as explained in Chapter Four. This reality makes silicon-based solar modules subject to frequent adjustments which increases the opportunity of learning (and un-learning) according to Badiru et, al. (Badiru, 2012).

In consequence, data on non-silicon solar PV modules (e.g.: thin film modules), and solar thermal energy are omitted because of their high current prices, compared to silicon-based modules, and lack of progress historically (de La Tour et al., 2013; Kavlak et al., 2018). There is no universal pattern as solar thermal, for example, is very location dependent. Most non-silicon modules have not experienced learning in the way silicon-based modules had and, accordingly, they have lower market share (Eising et al., 2020; Grafström & Poudineh, 2021).

With low installed capacity levels and low recent growth rates, their contribution to emissions reduction appears unlikely, with less possibility to establish a meaningful analysis based on them. They may well improve and play valuable roles several decades from now, but more information would be needed to determine whether their costs are likely to drop sufficiently.

Cost (price) measured in *Dollars per watt* will remain the baseline metric in analysing the competitiveness of solar products in the global market. Accordingly, data sources often provide average global cost (price) of all silicon-based modules' types under one variable, "Modules prices"[36], so it can be used in meaningful statistical analysis (Alberth, 2006; Candelise et al., 2013; Lafond et al., 2018; Rypdal, 2018). Solar PV modules information in the global markets are updated daily as any other commodity in the market.

Figure 5.2 summarises the variables used in this research and the steps taken to prepare each variable for the analysis:

[36] Reasons why price data is used instead of cost data were discussed in detail in Chapter Four

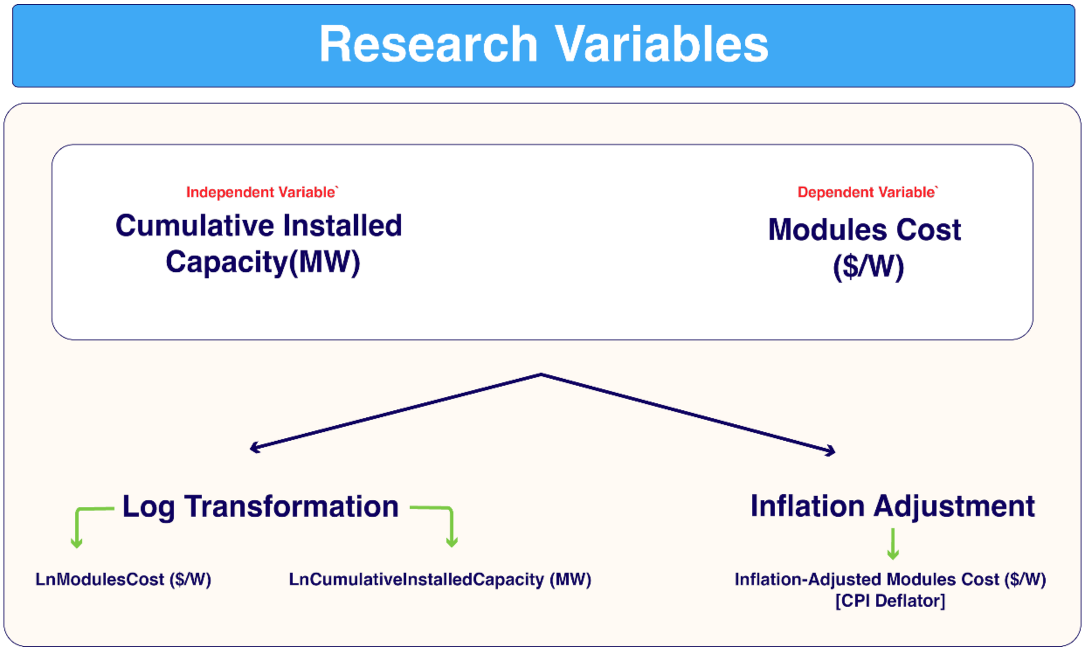

Figure 5.2: Summary of the variables used in the analysis

5.3.2 Uncertainty Concerning the Data Prior 1995

The choice of the dataset timeline used in this study (1996-2022) is linked to the emerging nature of the data at the early stages of the production process. This is seen in the data prior 1995 as stated in Chapter Four (Rypdal, 2018), where high uncertainty in the data, due to low installation and high prices, could negatively impact the quality and robustness of the models and add to the noise generated in the data. In fact, the first implementations of solar PV systems go back to the 1970s. In 1977, it cost $77 per watt for a simple solar cell. The high cost was accompanied by very low installations levels, which highlighted the trend in the solar industry of that era. In 1990, the first report of the IPCC (The Intergovernmental Panel on Climate Change) found that the planet has warmed by 0.5°C in the past century.

By 1996, a consensus position formed that greenhouse gases were deeply involved in most climate changes and human-caused emissions were bringing discernible global warming. It is when a new era has started for the renewable energy transition. Real changes in policies took place which positively affected the solar energy market growth. Accordingly, the first cost experience curve between 1976-1996 slowed down and a new curve started to form highlighted by large installations, economies of scale, and governmental subsidies and incentives, as shown in Figure 5.3:

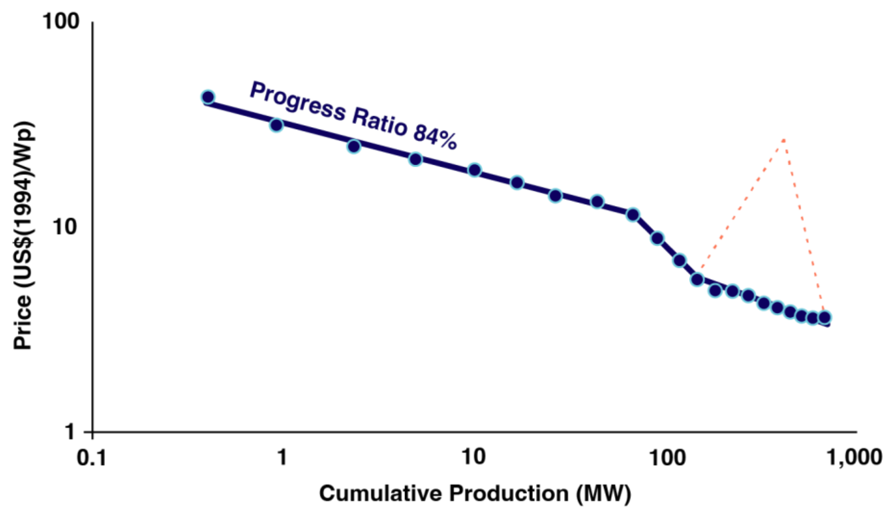

Figure 5.3: Solar PV installations between 1976-1995 (Source: (McDonald & Schrattenholzer, 2001)

To give weight for data with very low installation levels and high prices in current studies could be problematic in estimating and interpreting models especially for small sample sizes. It yet gets more complicated if the small sample is being split into training and validations subsets. The severe nonlinearity in solar PV data before 1995 resulted in a failed convergence, that often occurs due to poor selection of initial values for the non-linear models. As for Gompertz and the Logistic nonlinear iterative models, the initial value is one of the unknown parameters of the model, and its value is usually assumed a priori or calculated iteratively. In this research, this iterative process was repeated for data points between 1996 and 2017 until a solution converged.

This also means iteratively estimating the parameters until the sum of squared error (SSE) reaches a minimum[37] using the least-squares estimation. A solution converged when small changes in the experience

[37] Refer to section 5.5 for more details on the Sum of Squared Errors (SSE).

curve exponent "*b*" parameter were calculated between iterations. This process of iterative solving was adapted from Hu and Smith's "Accuracy Matters" (2013). Loss of convergence while estimating nonlinear models calls for certain modifications of the underlying computational model. To estimate initial values via an iteration process in the real world, it is likely to use software most of the time to perform this task.

5.3.3 Data and Log Transformation

High non-linearity in the data gives an early signal on the potential presence of non-stationarity (the data has a unit-root). Speaking of stationarity, data is considered stationary if it has a mean and a variance that doesn't vary over time (Hyndman and Athanasopoulos, 2018). Conversely, non-stationary datasets show strong trends or seasonality observed in the data over time. Non-stationarity can cause problems in statistical inference involving time series models and may give superior unrealistic results. As for experience curves models, potential reverse causality between the model's variables will give rise to non-stationarity over time (Chan & Wang, 2015).

Dealing with non-stationarity is highly recommended when performing regression analysis to understand the relationship between variables to build robust models. Therefore, logarithmic transformation is performed on both dependent and independent variables to smooth the data and eliminate stationarity effect (Wright, 1936; Papineau, 2006; de La Tour, 2012; Moore, 2015; Johnson, 2016; Hansen, 2017; Rypdal, 2018). It is one of the easiest modifications usually done to tackle non-linearity and non-stationarity in the data. It is important to mention that for non-linear models, the main purpose of using a log transformed variables is to tackle non-stationarity and to get a distribution that complies with the nonlinear regression assumptions, not to linearise the models.

Log transformation is one of the data transformation methods. Data transformation methods differ depending on the purpose of the data transformation. Transformation of data for least-squares regression greatly expands the utility of the analysis by allowing its application to nonlinear relationships. The generated variables used in the models for the purpose of this research are as follows:

[ln(InstalledCapacity)] generated from the original independent variable InstalledCapacity, and [ln(ModuleCost)] generated from the original dependent variable ModuleCost.

As mentioned before, when the original collected silicon-based solar PV modules prices ($/W) and the cumulative installed capacity (MW) were plotted against time, a significant trend becomes evident. Figure 5.4 below shows the original relationship between the two main variables used in the study. Nonlinearity is clear in the data with a flattening tail towards the bottom of the curve. This gives an indication of diminishing returns at the end of the production cycle and the rate of improvement is not constant over the life of the programme.

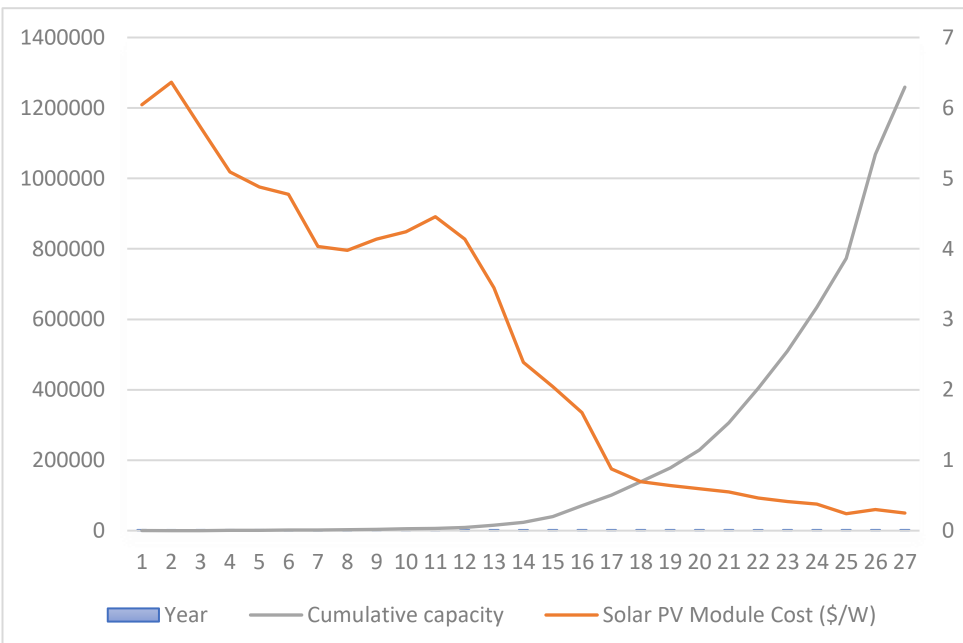

Figure 5.4: Cumulative installed capacity (MW) and module cost ($/W) against time

5.3.4 Data Standardisation: Choosing the Right Deflator

Once the data collection is done, the dataset will have to be standardised (Badiru, 2012; Moore, 2015; Johnson, 2016; Boone, 2018). Standardisation will occur by converting prior years values into a Base Year (BY), taking into account the effects of inflation for a fair comaprison.

There is a debate in literature on the best deflator to use. According to the *Eurostat* website[38], the choice of the deflator used for the elimination of prices changes is based on the nominal indicator which must be adjusted. Using the CPI values, the dataset for this research is in *Then Year dollars* (TY$) which are Base Year (BY$) inflated/deflated to represent the purchasing power of the funds if they were expended in that given year. The silicon-based Solar PV modules are standardised in this research to a Base Year (BY$96) value using the 2022 global CPI tables Federal Reserve Economic Data (FRED) Tables[39]. Price indexes are often constructed by government agencies[40].

Adjusting for inflation is done through three steps: acquiring the Base Year (BY) CPI value, finding the inflation adjustment factor in percentage between the reference period and a subsequent period, and dividing this factor by the original cost (price) in the database. Equations used to acquire the inflation-adjusted cost are:

$$\text{Inflation Adjustment Factor (CPI } YoY) = (\text{CPI } YoY_{n-1})*(1+(\text{CPI}_n/100)) \tag{5.1}$$

$$\text{CPI }\%_n = \text{CPI } YoY_n/100 \tag{5.2}$$

$$\text{Adjust cost for inflation} = \text{original module cost}_n/\text{CPI}\%_n \tag{5.3}$$

[38] https://ec.europa.eu/eurostat
[39] https://fred.stlouisfed.org/

[40] FRED database is one of them; it is an online database consisting of hundreds of thousands of economic time-series data from scores of national, international, public, and private sources. FRED's Consumer Price Index (CPI) tables are used in this research from FRED's databases.

The result adjusted cost is plotted against original dataset. The variation between inflation-adjusted cost and original cost is seen in Figure 5.5:

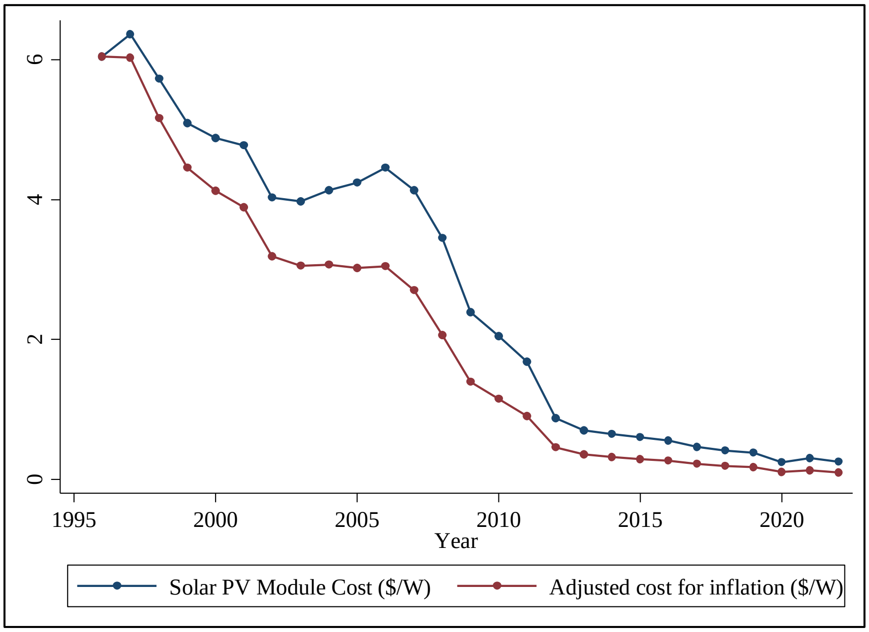

Figure 5.5: Module cost versus inflation-adjusted module cost ($/W)

5.3.5 Dataset Splitting: In and Out of Sample

It is important to evaluate forecast accuracy using genuine forecasts (Hyndman and Athanasopoulos, 2018). Yet, the reliability and the accuracy of forecasts can be better determined on new data that were not used when fitting the model to consider how well a model performs (Moore, 2015; Hyndman and Athanasopoulos, 2018). When choosing models, it is common for a researcher to separate the available data into two portions, training and test[41] data. The training data is used to estimate any parameters of the model using a forecasting method, and the test data is used to evaluate its accuracy. The test data is supposed to

[41] The test dataset is frequently referred to as validation dataset in this analysis.

provide a reliable indication of how well the model is likely to forecast on new data since it is not used in training the model:

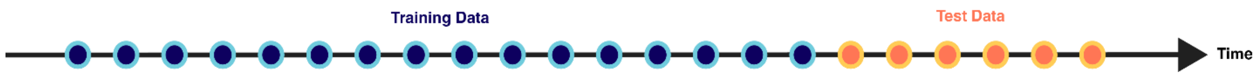

Figure 5.6: Data splitting timeline

There is no one answer on the size of each subset, but it mainly depends on how long the sample is and how far ahead the forecast is. However, the size of the test set is typically 20% of the total sample, with 80% in the training set (Kuvulmaz et al., 2005). It should be noted that a model which fits the training data well doesn't guarantee a good forecast. The same applies to adding more parameters to the model to achieve a better fit. Either way, an analyst should be careful of overfitting the model, which is as bad as failing to identify any systematic pattern in the data (e.g.: non-linearity). Over-fitting is a problem that comes with using the in-sample error (that results from the training dataset estimates) and it is related to over-optimism (Hyndman and Athanasopoulos, 2018).

The total data points used for this analysis is 27 (between 1996 and 2022). The training dataset contains 22 data points, with 5 data points left out for the model validation process. However, an analyst should treat the dataset carefully while deciding on data splitting. This becomes more relevant when the sample size is small, and splitting the data might negatively affect the performance of the model. Therefore, it is case-dependent whether to split the data or use all available observations which is also a valid approach followed in literature.

5.4 Experience Curve Models

5.4.1 Wright's Experience Curve Model

Since first used, the status quo for the experience curve models is Wright's model which takes the form of:

$$Y_n = Y_1 X^{-b} \tag{5.4}$$

where:

Y_1 = direct cost of first unit of production

Y_n = direct cost of n^{th} unit of production

X = cumulative volume of production

b = experience rate (%)

The model's specifications and the parameters of the model are detailed in both Chapter Three and Chapter Four. The two parameters that must be estimated are C_1 and b. In common cost estimating practice, b and Y_1 are determined through a linear regression[42] on a plot of the natural log of cumulative installed capacity *[ln(InstalledCapacity)]* against the natural log of the actual reported costs *[ln(ModuleCost)]*.

When applying linear regression models to data on technologies with falling costs, two features of the model must be stressed. First, the Wright's law model does not simply "assume" that if costs fell in the past then they will certainly fall in future. In practice, costs are predicted *to rise* with a non-zero probability that depends directly on observed data in the past. Second, despite the downward trends, all cost forecast distributions are always strictly positive since costs develop in a log-log space (Wright, 1936 Way et al., 2019).

[42] More details on the regression technique used can be found in the following section (5.5) of this chapter.

5.4.2 Gompertz Experience Curve Model

Gompertz model is one of the contemporary experience curve models considered for comparison in this research as explained in detail in Chapter Four. Gompertz model has been used for long as a growth curve before it has been used as an experience curve. The nature of growth rate in this model is exponential; which makes faster than other curves to reach the maximum level and slow down to the flat area of the curve (Buchanan et al., 1997; Akın et al., 2020). Gompertz model has different forms but, for actual purposes and ease of use, a recent form has been developed which is widely used today. For the sake of this analysis, it is represented in regression analysis by:

$$Y_i = \beta_0 + \beta_1 * exp(-exp(-\beta_2 * (X_i - \beta_3))) \quad (5.5)$$

Where:

Y_i = Cumulative average cost of producing x units (solar PV modules in this case)

X_i = Cumulative installed capacity

β_0 = location parameter (added to allow for smooth conversion)

β_1 = Upper Asymptote (Maximum installed capacity)

β_2 = Slope factor

β_3 = Experience rate

Slope of the curve is expected to be positive for finite values of x and approaches zero for infinite values of x (Akın et al., 2020). The decay factor is one of the properties that defines Gompertz model's usefulness. The decay factor in Gompertz model highlights the effects of diminishing technological learning.

Winsor (1923) explained the need for four constants to introduce skewness into a growth curve, and to allow for a successful convergence and iteration of the model. In this analysis, adding a fourth parameter (the constant parameter) to Gompertz model was useful given the small size sample and the data splitting which makes the data set used to train the model even smaller.

5.4.3 The Logistic Experience Curve Model

According to Walk (2012), "researchers in the United States such as Lenz (Lenz, 1985), Martino (Martino, 1972, 1973), and Vanston (Vanston, 1988), and others around the world, such as the very prolific Marchetti (Marchetti 1977, 1994, 1996) refined forecasting methods and showed that the logistic model was an excellent construct for forecasting technological change".

In the late 20th Century, "the logistic displayed virtually universal application for modelling technology adoption, as well as for modeling effectively many other individual and social behaviors" (Walk, 2012). The logistic curve is given by:

$$Y_i = \beta_0 + \beta_1/(1 + \exp(-\beta_2 * (X_i - \beta_3))) \tag{5.6}$$

Where:

Y_i = Cumulative average cost of producing x units (solar PV modules in this case)

X_i = Cumulative installed capacity

β_0 = location parameter (added to allow for smooth conversion)

β_1 = Upper Asymptote (Maximum installed capacity)

β_2 = Slope factor

β_3 = Growth rate

The same observation on adding the fourth parameter (the constant parameter) applies to the Logistic curve to achieve a valid comparison between the models. This also allowed for a successful convergence and iteration of the model, given the small size sample and the data splitting which makes the data set used to train the model even smaller.

5.5 Analysis Methods

In the social sciences studies, it is an accepted practice to test specific theoretically driven research hypotheses using formal statistical procedures. There is a wide range of quantitative forecasting methods that were developed within specific disciplines for specific purposes. Each method has its own characteristics, accuracies, and costs that must be considered when choosing a specific method.

Most quantitative prediction problems use either time series data (collected at regular intervals over time) or cross-sectional data (collected at a single point in time). They are used to estimate certain parameters of interest, and their relevant standard errors individually across different experimental conditions, and to observe whether the resulted pattern of parameter estimates supports or contradicts some proposed hypothesis (Kuvulmaz et al., 2005; Qureshi et al., 2020).

5.5.1 Regression Analysis

Probabilistic mathematical modelling is the central analytical technique employed in this study. In general, a probabilistic model or function is one that has a deterministic aspect as well as a random error component (McClave and others, 2014).

The functions used to model the data are often the basis of the deterministic component. As a consequence, the random error is found through the regression analysis techniques. The *basic* concept is that the time series, *y*, forecast assuming that it has a linear relationship with other time series, *x*.

Regression analysis commonly models the relationships between a response variable and one (or more) predictor variables. Based on the values of the predictors, a regression model is commonly used to understand how changes in the predictor values are associated with changes in the response mean.

The simplest functional form of the regression model allows for a [linear] relationship between the dependent (forecast) variable *y*, and a [single] independent (predictor) variable *x*, to estimate the model's parameters, β_0 and β_1:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{5.7}$$

Figure 5.7 shows an example of a result from such a model. The coefficients β_0 and β_1 denote the intercept and the slope of the line respectively. The intercept β_0 represents the predicted value of *y* when $x = 0$. The slope of the model, β_1, represents the average predicted change in *y* resulting from a one unit increase in *x*. Each observation can be seen as the explained part of the model, $\beta_0 + \beta_1 x_t$, and the random "error", the residuals, ε.

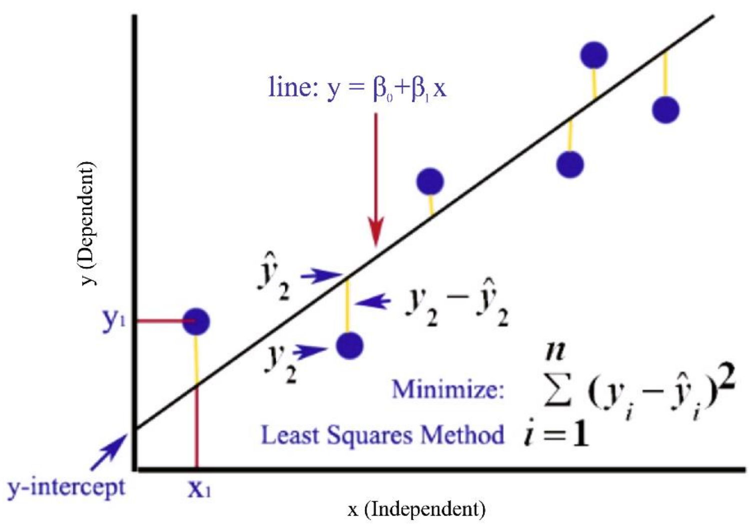

Figure 5.7: Simple linear regression outcome

The “error” term does not necessarily imply a mistake in the model, but rather a deviation from the underlying straight-line model. It normally captures all the other elements that affect the dependent variable plus any random elements.

Regression analysis was chosen for various reasons such as: First, the long history of reliable and good forecasts that regression analysis has in literature (McDonald & Schrattenholzer, 2001; Kuvulmaz et al., 2005; Papineau, 2006; Akın et al., 2020; Nagy et al., 2013; Moore, 2015; Johnson, 2016; Hansen et al., 2017; Rypdal, 2018). Second, for small sample sizes, regression analysis showed less bias than other estimation techniques such as the *Maximum Likelihood (ML)* estimation which, despite its reliability as an estimation method, can be heavily biased for small samples.

There are a variety of regression techniques that are available based on the research question, the type of response variable, the type of model that is required to provide an adequate fit to the data to answer the research question, and the estimation method. The correct use of regression models techniques, in general, requires that several critical assumptions be satisfied based on the chosen regression method as follows.

5.5.2 Least Squares Estimation Method

In practice, the values of the coefficients $\beta_0, \beta_1, \ldots, \beta_k$ need to be estimated based on a collection of observed data. The least squares principle provides a way of estimating the coefficients effectively by simply minimising the sum of the squared errors as follows:

$$SSE = \sum \varepsilon^2_t = \sum^n_{i=0} (y_i - f(x_i))^2 \tag{5.8}$$

Where:

SSE – Sum of Squared Error

y_i – the i^{th} value of the variable to be predicted

$f(x_i)$ – the predicted value

x_i – the i^{th} value of the explanatory variable

The sum of squares in statistics is a tool that is used to evaluate the dispersion of a dataset. This estimation technique is named the least squares estimation as it gives the least value possible for the sum of squared errors (SSE). The goal is to minimise the sum of squared errors (SSE) of the regression model to test how well a model estimates the coefficients based on a given set of data. The process of finding the best estimates of a coefficient is often called "fitting" the model to the data, or "training" the model (Young & Keith Ord, 1985). Estimated coefficients are referred to using the notation $\hat{\beta_0}, \hat{\beta_1}, \ldots, \hat{\beta_k}$. The value of the sum of squared errors (SSE) is calculated by taking the vertical distance between the actual data point and the prediction line. The rule of thumb is as follows: the smaller the sum of squared errors, the better the model, indicating less variation in the data (Moore, 2015; Boone, 2018).

Depending on the functional form of the model, the least squares technique can take different approaches to provide the most accurate estimation. Famous types of this technique are the Ordinary Least Squares (OLS), for linear models' estimations, and the Nonlinear Least Squares (NLS), for nonlinear models' estimations (Gulledge et al., 1990; Chan & Wang, 2015). Both techniques were needed in this comparative study given the different types of models used.

(a) Linear Least Squares Estimation Method (Ordinary Least Squares OLS)

The ordinary least squares (OLS) method is a type of linear regression technique that is used to estimate the unknown parameters in a linear regression model. As explained earlier, the method relies on minimizing the sum of squared residuals between the actual and predicted values (Young & Keith Ord, 1985; Badiru, 2012). The Ordinary Least Squares (OLS) is the most popular method in least squares estimation technique, because it is easy to use and yet produces decent results.

The previously mentioned simple linear regression mathematical form, with a single regressor (independent variable) *x* that has a relationship with a response (dependent or target) y, is the standard equation of the OLS procedure:

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon \tag{5.9}$$

Where:

β_0: Model intercept

β_1: Slope (unknown constant)

ε: Random error component

The outcome is a line where *y* is the predicted dependent variable, *x* is the independent variable, and β_0 and β_1 are the estimated coefficients. There are assumptions that should be implicitly made about the model and the error values when using linear regression models (Moore, 2015).

As for the model, it is assumed that the model is a reasonable approximation to reality, and that the relationship between the forecast variable, *y*, and the predictor variable, *x*, satisfies a linear relationship (Badiru, 2012). Consequently, the predictor variable, *x*, *should not be a random variable*. The nature of most observed data in business and economics is the reason behind the existence of the latter assumption. Contrary to controlled lab experiments, it is not typically easy to control the value of the variable *x* in observational time-series data.

As for the error values, there is no consensus on the number of the assumptions, yet many can be found in literature. However, there are key assumptions that are well-known to be the most important such as:

1. **Linearity:** The relationship between *x* and *y* must be linear in parameters of the specific functional form chosen. This assumption is usually checked by examining a scatterplot of *x* and *y*. If the scatter plot follows a linear pattern (i.e., not a curvilinear pattern), it shows that the linearity assumption is met (de La Tour et al., 2013; Elshurafa et al., 2018). If non-linearity persisted, then non-linear transformations of independent variables of the regression can be done by taking, for example, *logX* instead of *X* as the independent variable, and then check for linearity. The same applies to the dependent variable which will be *logY* in this case (Moore, 2015).

2. **Independence/ No Autocorrelation:** this means there is no relationship between the residuals and the predicted values. This assumption is firstly checked by examining a scatterplot of "residuals versus predicted values." The correlation should be approximately zero, otherwise, the result of the forecast is considered inefficient since there is more information in the data that is left behind (de La Tour et al., 2013).

   Autocorrelated errors signal model misspecification. Ideally, model errors should be *i.i.d* (independent and identically distributed), which means they should have no patterns in them. If they do, there is some information left unextracted; some more modelling can be done to extract the pattern (Honious et al., 2015).

   The first step is to test for autocorrelation in residuals. A popular test among practitioners is the well-known Durbin-Watson (DW) test. The Durbin-Watson test generally follows a reasonably easy procedure (Badiru, 2012). The DW statistic ranges from zero to four, with a value of 2.0 indicating zero autocorrelation. Values below 2.0 mean there is positive autocorrelation and value above 2.0 indicate negative autocorrelation. However, it should be performed with caution as it performs poorly except for long time series and large autocorrelation (Turner et al., 2020).

Autocorrelated errors, if found, should be handled correctly to ensure reliable outcomes. The Newey-West (NW) estimator is frequently used to overcome autocorrelation in residuals of the regression model often applied to time series data while keeping the original model. “The NW estimator of the variance of the regression parameters estimated using OLS accommodates autocorrelation and heteroskedasticity of the error terms in the regression model” (Turner et al., 2020). It is one of the so-called heteroscedasticity and autocorrelation consistent (HAC) estimators of the covariance matrix. It is not the only estimator available, yet it works for any combination where heteroscedasticity and autocorrelation are present. The Newey-West (NW) test should be available in any major statistical software package (Badiru, 2012; Rypdal; 2018).

3. **Normality:** It is usually useful, *but not necessary*, to have the errors normally distributed to easily produce prediction intervals. However, this assumption is more critical for small sample sizes than for larger sample sizes. Therefore, it was tested graphically using a histogram to visually observe normality. Also, it was statistically tested using the famous Shapiro-Wilk test for normality. The hypotheses of this test are as follows:

H_0: *Residuals are normally distributed*

H_1: *Residuals are not normally distributed.*

Should the resulted *p*-value support the rejection of the null hypothesis, normality cannot be assumed in residuals. Otherwise, if the null hypothesis was accepted, residuals would be considered normally distributed. It is worth mentioning that the normality assumption applies to the distribution of residuals not to the data distribution (Hyndman and Athanasopoulos, 2018; Turner et al., 2020).

4. **Homoscedasticity:** Homoscedasticity is an assumption of equal or similar variances in different groups being compared. If errors are heteroscedastic (i.e. OLS assumption is violated), the forecasts will be considered biased. To elaborate, the standard error is central to conducting significance tests and calculating confidence intervals, which means biased standard errors often lead to incorrect conclusions about the significance of the regression coefficients. The impact of violating the assumption of homoscedasticity is a matter of degree, increasing as heteroscedasticity increases.

Many statistical packages provide an option of robust standard errors to correct this bias. One approach for dealing with heteroscedasticity is to transform the dependent variable using one of the variance stabilizing transformations (e.g.: Logarithmic transformation) (Hyndman and Athanasopoulos, 2018). Figure 5.8 shows a simple graphical presentation of homoscedasticity and heteroscedasticity:

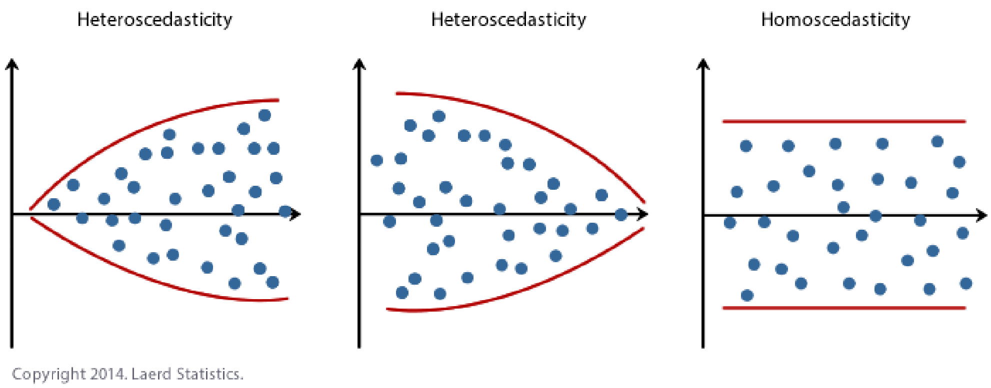

Figure 5.8: Simple graphical representation of homoscedasticity and heteroscedasticity (Source: Laerd Statistics)

(b) Non-Linear Least Squares (NLS) Estimation Method

In many circumstances, nonlinear models cannot be avoided. The nonlinear model theory is derived from the classical linear model, in which at least one parameter is not specified in a linear manner. It extends linear least squares regression for use with a much larger and more general class of functions. As for the scope of this research, nonlinear models are analysed, hence it explains the importance of providing more details on this estimation method.

Although the linear relationship, discussed so far in this chapter, is often adequate, there are many cases where a nonlinear functional form is found more suitable. To keep things simple in this section, the Single Factor Experience Curve (SFEC) model is used, with one predictor x. The simplest way of modelling a nonlinear relationship is to log-transform the forecast variable y and/or the predictor variable x before estimating a regression model.

The goal of the Non-Linear Least Squares (NLS) estimation is the same as the Ordinary Least Squares (OLS): to minimise the sum of squared residuals between the actual and predicted values. The nonlinear least squares (NLS) estimator is known to be asymptotically unbiased. In this research, as in several research papers, the Gauss–Newton algorithm is specifically used to solve non-linear least squares problems, which is equivalent to minimizing a sum of squared function values. It is an extension of Newton's method for finding a minimum of a non-linear function.

The Gauss-Newton method is an iterative algorithm to solve nonlinear least squares problems. “Iterative” means that the algorithm uses a series of calculations (based on guesses for x-values) to find the solution. It is a modification of Newton’s method, which finds x-intercepts (minimums) in calculus. The Gauss-Newton is usually used to find the best fit theoretical model although it could also be used to locate a single point (Srinivasan & Mason, 1986; Stock & Watson, 1998). Given the complicated nature of the non-linear least squares procedure, it is almost exclusively performed with software.

Assumptions on nonlinear regression models heavily depend on your model and how you want to estimate your model. Yet, there are key assumptions that need to be met in the presence of the Nonlinear Least Squares (NLS) method:

1. The most relevant assumption of Nonlinear Least Squares (NLS) is that the model fits the data well. Data might suggest the model is too complex for the data, and a simpler model should be considered (Boone, 2018).
2. **Normality:** As defined and tested in the previous section, normality assumption is recommended for the Nonlinear Least Squares (NLS) estimated residuals. However, Motulsky and Christopoulos (2003) argued that the normality assumption is not necessary for nonlinear regression. It is often used because it's convenient. Normality is tested for non-linear models following the same tests as previously explained in section (Motulsky and Christopoulos, 2003)**.**
3. **Homoscedasticity:** Again, the variances should be the same regardless of the predicted values. The variance of the residuals should be consistent in predicted values. This assumption is examined by performing the scatterplot of "residuals versus fits." The variance of the residuals should be consistent across the *x*-axis. If the plot shows a pattern, then variances are not consistent, and this assumption has not been met (Badiru, 2012; Boone, 2018).

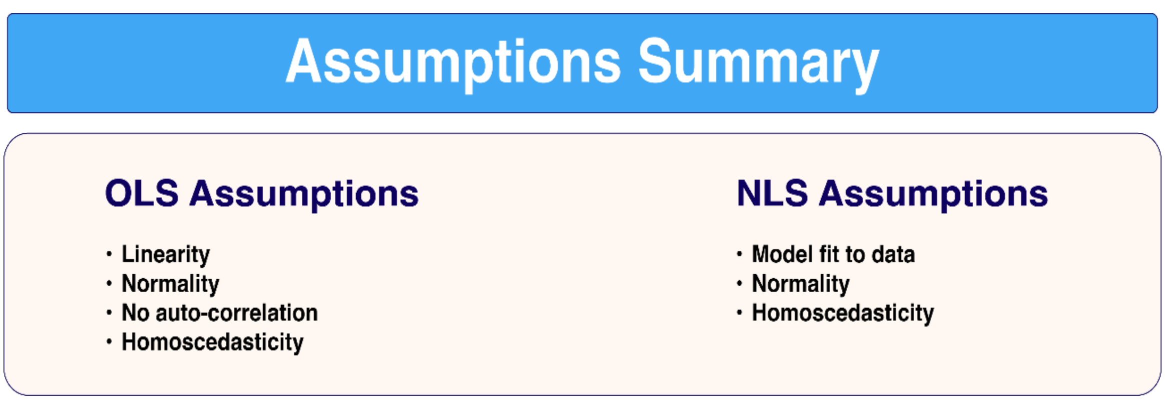

Figure 5.9: Assumptions summary for regression models errors

5.6 Evaluation Metric for Regression Models

5.6.1 Fitted Values and Goodness-of-fit

An observation in a time series can be forecast using previous observations. This is what is commonly called **fitted values**. They are donated by $\hat{y}_{t-1}$ and they always involve one-step forecasts. The hat above the y reminds us that this is an estimate (Moore, 2015).

A commonly used approach to summarise how well a regression model fits the data is to calculate the coefficient of determination, or R^2. It is the square of the correlation between the observed values y, and the predicted values $\hat{y}$, and is written as follows:

$$R^2 = \Sigma(\hat{y}t - \bar{y})^2/\Sigma(y_t - \bar{y})^2 \tag{5.10}$$

The result reflects the proportion of variation in the forecast variable that is accounted for (or explained) by the regression model. R^2 lies between 0 and 1. If the predictions of the model are close to the actual values, then R^2 is expected to be close to 1 (assuming there is an intercept).

5.6.2 Standard Error of the Regression: The Residuals

The "residuals" in a time series model are typically what is left over after fitting a model. It is, for most time series models, the difference between the observations, y_t and the corresponding fitted values, $\hat{y}_t$:

$$e_t = y_t - \hat{y}_t \tag{5.11}$$

The standard deviation of the residuals, which is often known as the "residual standard error" is another measure of how well the model has fitted the data. The lower the value of the residuals, the better the model's forecast. The residuals are uncorrelated, or they should be (IEA, 2000). Correlations between residuals indicate that there is information left in the residuals that should have been used in computing forecasts. Moreover, as mentioned earlier, the residuals have zero mean, otherwise the forecasts are biased (Hyndman and Athanasopoulos, 2018). If either of these properties was not met, then the forecasting method should be improved to give better forecasts. However, that does not mean that forecasting methods that satisfy these properties are necessarily the best.

In addition to the graphical plots, there is an array of plots that can be produced, to double check the underlying assumptions of the model, and understand the outcomes of the model by analysing the residuals:

Breusch-Godfrey Test

When fitting a regression model to time series data, a useful test of autocorrelated errors in the residuals is the Breusch-Godfrey test, which is designed to detect serial autocorrelation. It works on the basis of testing the joint hypothesis that there is no autocorrelation in the residuals up to a given confidence level. A small *p*-value indicates there is significant autocorrelation present in the residuals (Hyndman and Athanasopoulos, 2018).

Histogram and Kernel Density Estimation for the Residuals

Histograms are useful and easy solution to check whether the residuals are normally distributed or not. Although the normal distribution assumption is not essential for forecasting, it does make the intervals prediction much easier (Moore, 2015; Hyndman and Athanasopoulos, 2018).

Plotting Residuals Against Predictors and Fitted Values

Residuals are expected to be randomly scattered with no systematic pattern present. A simple way to check this is to establish scatterplots of the residuals against each of the predictor's variables. Should the scatterplots show a pattern, the model would need to be modified accordingly (Alberth, 2006; Papineau, 2006; Badiru, 2012; Moore, 2015).

Another plot of the residuals against the fitted values should also show no pattern. A pattern in this plot may indicate the presence of "heteroscedasticity" in the errors (Moore, 2015; Johnson, 2016). Heteroscedasticity implies that the variance of the residuals may not be constant over time, which requires an appropriate transformation of the predictor variable such as a logarithmic, square root, and so on (Moore, 2015; Rypdal, 2018).

5.6.3 Forecast Errors

As mentioned before, a forecast error doesn't usually mean a mistake, it simply means the difference between an observed value and its forecast, which is the unpredictable part of an observation (Badiru, 2012). Forecast errors, in practical, are calculated using the residuals, yet they are different in many ways. As for the scope of this research, the following forecast error metrics are used:

A. Scale-dependent Errors

The two most used scale-dependent measures are based on the absolute errors or squared error are the Mean Absolute Error (MAE), and the Root Mean Squared Error (RMSE). The MAE is a useful measure widely used in model evaluation, while the RMSE has been frequently used as a standard evaluation metric to measure model performance in many climate research studies (Hodson, 2022). Equations used for both measures calculations are as follows with y_n as the observed value, $\hat{y}_t$ as the predicted value, and n as the number of observations:

$$\text{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \tag{5.12}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{5.13}$$

They have both been used to assess model performance for many years, there is, however, no consensus on the most appropriate metric for models' errors, with a historical argument favouring one metric or the other. The choice of error metric should meet with the expected probability distribution of the errors; otherwise, any inference will be biased. For example, RMSE is optimal for normal (Gaussian) errors, while MAE is optimal for other error distributions, and so on (Hyndman and Athanasopoulos, 2018).

B. Percentage Errors

Percentage errors typically have the advantage of being unit-free, and so are used to compare forecast performances between different data sets. The Mean Absolute Percent Error (MAPE) is one of the most used measures and is usually calculated as:

$$M = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \tag{5.14}$$

Where:

M – Mean Absolute Percent Error (MAPE)

n – Number of observations

A_t – Actual value

F_t – Forecast value

MAPE is considered one of the best measures of forecast accuracy. In MAPE's equation, the absolute value is taken to avoid any cancellation between positive and negative error values which can affect the accuracy of the model (Bailey et al., 2011; Moore, 2015). MAPE provides a unitless measure of accuracy and can be interpreted as the average percentage error of the model.

Expressed as a percentage, it allows a comparison of how the model works and the accuracy of different experience curve models. MAPE typically takes the same error term that is found in the Sum of Squared Error (SSE) equation and divides it by the actual value of the unit, then takes the mean (arithmetic average) of all of the data points. The rule of thumb is: *Lower the MAPE, better fit is the model*. However, there is no specific number that can be considered as the right number for MAPE.

MAPE is the main metric on which the research hypotheses are built. Therefore, if contemporary models reduced both SSE and MAPE when compared to the SSE and MAPE of Wright's prediction, then a conclusion could be made that the contemporary models would be a more accurate model to use when conducting experience curve analyses (Moore, 2015; Boone, 2018; Hyndman and Athanasopoulos, 2018).

MAPE is robust to outliers, so the effects of outliers do not extremely influence this measure. The output of the MAPE's equation is used in this research to evaluate the forecasting performance of the competing models.

5.7 Research Hypotheses Testing

The theory behind this comparative study is that cumulative installed capacity, and module prices data may provide a more realistic assumption for solar PV growth and eventually a more accurate predictor of actual costs using a modern experience curve model (Moore, 2015; Rypdal, 2018). The main hypothesis states that the Mean Absolute Percent Error (MAPE) is significantly different between the predicted module prices for alternative models (Gompertz and the Logistic models) when compared to the conventional

Wright's model. MAPE, as previously explained, is ultimately defined as the average measure of variation that takes the error both positive and negative as a percentage (Hyndman and Athanasopoulos, 2018).

5.7.1 Research Hypotheses

As stated in the introduction of this research, this thesis mainly aims to answer the following questions:

1. Can any of the contemporary experience curve models be applied to current solar PV modules cost estimating procedures? If so, which ones?
2. Are experience curve models that account for diminishing learning rates more accurate than the conventional experience curve model used toady? If so, which ones?
3. Which experience curve model is most accurate, with least forecasting error, at predicting the actual cost of solar PV modules?

Here are the hypotheses that were developed and tested to complete the statistical comparison between the three experience curve models. They can be summarised as follows:

H_1: One or more of the three experience curve models has a MAPE significantly different from the other models.

H_2: One or more of the alternative experience curve models is significantly more accurate than Wright's model in predicting solar PV modules costs (have significantly lower MAPE).

H_3: The nonlinear model, which accounts for both previous experience and the flattening effect, has the lowest MAPE as the most accurate predictor of solar PV modules costs.

The hypothesis is a simple proposition that can be proved or disproved through various scientific techniques. It establishes the relationship between independent and some dependent variables. It is capable of being tested and verified to ascertain its validity, by an unbiased examination. Testing of a hypothesis attempts to make clear whether or not the supposition is valid (Badiru, 2012; Hyndman and Athanasopoulos, 2018).

The null hypothesis (H_0) for the first hypothesis in this analysis is that $\mu_1 = \mu_2 = \mu_3$, which means all of the MAPE values are the same, against the alternative hypothesis (H_1) that al least one the three models has a mean that is significantly different. If the null hypothesis can be rejected, with enough evidence to support a significant difference, then the next step is to test each of the contemporary experience curve models against the conventional model.

The second null hypothesis (H_0) mathematically states that $\mu_1 = \mu_i$, where $i = 2,3$. This hypothesis is tested against the alternative hypothesis (H_1) that $\mu_1 > \mu_i$. These hypotheses test whether at least one of the alternative experience curve models has MAPE that is significantly lower than the conventional model.

The final test is for the third hypothesis which will investigate which of these alternative models, that have provided significantly smaller mean errors from the conventional model, is the best predictor. The third null hypothesis (H_0) states that $\mu_i = \mu_j$, where i and j are both significantly lower than μ_1. This hypothesis is to be tested against the alternative hypothesis (H_1) that $\mu_i < \mu_j$. That analysis will provide an answer to the initial question of this thesis of determining if there is an alternative best fit model that is more accurate than Wright's model.

5.7.2 Hypotheses Testing

Hypothesis testing is the act of testing an assumption regarding a population parameter (Bailey, 2011). The methodology used by the analyst was basically determined based on the nature of the data used and the main study hypotheses. Some of these tests require certain assumptions to be met, otherwise they can't be used. Tests that make assumptions about the parameters of the population distribution from which the sample is drawn, are called *parametric tests*. Typically, this is the assumption that the population data are normally distributed. On the contrary, *non-parametric tests* are “distribution-free” and, consequently, can be used for non-Normal variables.

Once the Sum of Squared Error (SSE) and Mean Absolute Percent Error (MAPE) values were calculated for each experience curve equation, hypotheses are tested to determine whether the difference between the error values between the three functional forms were statistically different. First, it is important to understand the behaviour of the data to determine whether parametric or non-parametric tests are supposed to be used. The Absolute Percent Error (APE) values, derived from the validation data subset results, are used to test hypotheses as follows:

As for **the first hypothesis**: a statistical test is needed to determine whether at least two of the populations means are statistically different from each other. One-Way ANOVA and Kruskal methods are frequently used for testing whether samples originated from the same distribution (Moore, 2015; Boone, 2018).

The parametric One-way ANOVA (ANalysis Of VAriance) is a statistical test to determine whether two or more population means are different. In other words, it is used to compare two or more groups to see if they are significantly different. The Kruskal-Wallis is the non-parametric method used to compare *k* independent samples. It is roughly equivalent to a parametric one-way ANOVA with the data replaced by their ranks.

The choice between parametric test (One-way ANOVA) and non-parametric test (Kruskal-Wallis) is made based on the assumptions of each method. One-way ANOVA requires three conditions for valid results. The first condition is related to the random selection of the samples from the population. The second condition is that the samples must have an approximately normal distribution. Lastly, the population variances must be equal (Moore, 2015).

As for the randomness assumptions, samples are considered random as there was no specific selection process from the data samples collected. Next, the normality of the data is here tested for the three samples using the previously mentioned Shapiro-Wilk test for normality as follows:

H_0: APE values are normally distributed

H_1: APE values are not normally distributed.

Should the resulted *p*-value support the rejection of the null hypothesis, normality cannot be assumed in the absolute percent error sample. Otherwise, if the null hypothesis was accepted, then the absolute percent error would be considered normally distributed (Turner et al., 2020).

Equality of variance, the third assumption, is tested by simply dividing the largest sample standard deviation by the smallest standard deviation (Moore, 2015). The equality of variances is tested by dividing the largest sample standard deviation by the smallest standard deviation. For example, suppose sample 1 has a variance of 24.5 and sample 2 has a variance of 15.2. The ratio of the larger sample variance to the smaller sample variance would be calculated as 24.5 / 15.2 = 1.61. As a rule of thumb, if that resulted value is 4 or less, then the variances can be assumed equal.

If these conditions are not met, a non-parametric test will be used to investigate the first hypothesis of this analysis. The non-parametric Kruskal-Wallis test does not assume normal distribution of the underlying data. The result of this test is an *f*-statistic falling within a *Chi*-distribution.

Once the values are filled in tables, checked, and populated, the first hypothesis will be checked on whether $\mu_1 = \mu_2 = \mu_3$ of the three tested models, by comparing the set of mean absolute percent errors using either an ANOVA or Kruskal-Wallis test. The hypotheses would be as follows:

H_0: the mean ranks of the groups are the same (no significant statistical difference)

H_1: the mean ranks of the groups are not the same (mean ranks are statistically different)

The second hypothesis indicates that at least one of the alternative models is more accurate by having a lower MAPE than Wright's model MAPE. Dunnett's method is a particularly useful method to analyse samples, while having control groups, based on modified *t*-test statistics (Dunnett's *t*-distribution). It is a powerful statistic and, therefore, can discover relatively small but significant differences among groups or combinations of groups (Moore, 2015). As Dunnett's compares two groups, it acts similarly to a *t*-test. The Dunnett test is used by researchers interested in testing two or more experimental groups against a single control group. It is worth mentioning that Dunnett's test is non-parametric and doesn't require that the assumption of normal distribution and equal variances to be met.

If the outcome of the second hypothesis showed a significant result, the next step in the post hoc analysis will be to test **the third hypothesis** on which model is most accurate. A paired difference *t*-test is necessary to answer this question. This choice was made because the paired *t*-test statistical test is a widely accepted statistical method used to test whether the mean difference between pairs of measurements is zero or not. It is a comparison of two different methods of measurement or two different measurements where the measurements are applied to the same subjects (Boone, 2018).

This *t*-statistic typically falls within a student-*t* distribution that can either support or reject the null hypothesis given a certain confidence level. Paired *t*-test estimate has the following hypothesis:

H_0*: the mean of the paired differences equals zero in the population*

H_1*: the mean of the paired differences does not equal zero in the population.*

If the *p*-value is less than 0.05 (the significance level), then there will be enough evidence to reject the null hypothesis. This will lead to a conclusion with strong evidence that the mean paired difference does not equal zero in the population (Moore, 2015). To successfully perform a parametric paired *t*-test, the distribution of differences between the paired measurements should be normally distributed. Also, equal variances assumption should be met. It is the same assumption that was previously checked for parametric One-Way ANOVA test in hypothesis one.

However, if there was a concern about data being non-normally distributed, the Wilcoxon-Mann-Whitney test will have more power than the *t*-test in this case. It is a 2-group non-parametric comparison test equivalent to the parametric *t*-test that can be used to test treatment effects when data are not normally distributed. Wilcoxon-Mann-Whitney test computes a *z*-score, and the corresponding probability of the *z*-score for the sum of the ranks within the two groups (Turner et al., 2020). Also, the Wilcoxon-Mann-Whitney test will have comparable power if the data are normally distributed.

The hypotheses for a Mann-Whitney test are as follows:

H_0: the two populations are equal,

H_1: the two populations are not equal.

As for this study, the confidence level of 95% will be used with an α of 0.05. This α means here that *f*-statistic or t-statistic with a resulting *p*-value < 0.05 will reject the null hypotheses and provide evidence that supports the alternative hypothesis (that the mean values between the models are different).

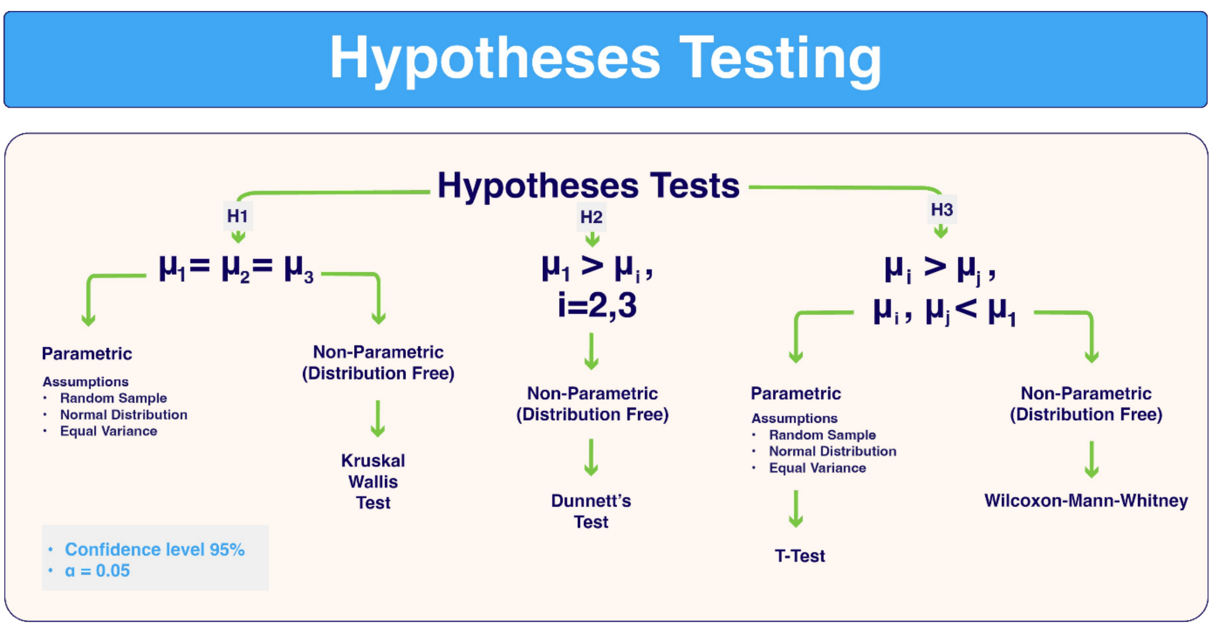

Figure 5.10: Summary of research hypotheses testing process

5.8 Testing Structural Changes and Coefficients Stability

5.8.1 Structural Breaks Estimation Framework

This section covers methodological approaches related to estimation, testing and computation of potential structural breaks in the models. Structural breaks have been observed in many economic and financial time series according to Stock and Watson (1996). Identifying structural breaks, or change points, is a crucial step in time series analysis where a key assumption is that the coefficients do not change over time (Boot and Pick, 2017; Casini et al., 2018). Hence, this assumption is unlikely to hold over time, and the model parameters might change as a result of major disruptive events. Parameters instability can have harmful impact on estimation and inference and can potentially lead to costly errors in decision-making (Ditzen et al., 2022).

Structural breaks in a model serve as one possible reason for poor forecast performance in out-of-sample forecasts (Casini et al., 2018). A fixed parameter model cannot be expected to forecast well if the true parameters of the model change over time. Conversely, if the model isn't forecasting well, it may be worth considering if model instabilities could be playing a role (Leeb, 2008).

In this analysis, and within the validation data points, there are two important factors that require more investigation on the impact they might have had on the accuracy of the models forecast. The first factor is related to the reduced policy support for deployment in China that hit the global solar PV market in the second half of 2018. As China is by far the world’s largest solar market, the effect of these policies was expected to spread globally. “Oversupply is universal”, according to a note by Bloomberg New Energy Finance (BNEF) which predicted a market panic in the short term (BNEF note, 2018).

This was followed by the global Covid-19 pandemic at the end of 2019 which affected global shipping prices and supply chains at many levels (Ditzen et al., 2022). With lockdown taking place in most countries, shipping prices skyrocketed, and commodities prices struggled to stay resilient. Therefore, years from 2018 on towards the end of the forecast period represent a point of interest to be tested for possible unusual deviation and coefficients stability.

Testing for structural breaks represents a rich area of research. The test for structural breaks and which test to implement depends on several factors (Boot and Pick, 2017). For example, among the most important factors is whether the break date is known for the analyst or not. Therefore, it is essential to understand the statistical characteristics of both the breaks and the data to ensure the plausible method is implemented (Ditzen et al., 2022).

5.8.2 Dummy Variables and Chow Test

A dummy variable is a variable which takes the value of 0 except in the one observation for a specific date (Ditzen et al., 2022). Dummy variables are broadly used to include numerous potential effects on the model. They can be used to identify seasonal effects, changes in intercept, and changes in the slope of the regression line (Leeb, 2008).

The dummy variable approach to testing for a structural break implies running two regressions. The first is the basic restricted model without the dummy variables, then the second model is the unrestricted version of the model including the intercept, the slope and dummy variables. This is followed by the usual *f*-test testing for the difference between the two models (Boot and Pick, 2017). By estimating the coefficients separately using two separate sub-samples, it is possible to obtain a better fit to the data.

In this case, a dummy variable taking the value 0 before 2018 and 1 afterwards could then be used to represent potential structural breaks effect.

Time = 0 if year <= 2018

Time = 1 if year > 2018

Since the break date is known, the Chow test is used to examine whether the model's parameters of one group are different from those of other groups. A Chow test (1960) is a statistical test developed by economist Gregory Chow that is used to test whether the coefficients in two different regression models on different datasets are equal at some point. It is built on the theory that if parameters are constant then out-of-sample forecasts should be unbiased.

Chow test uses an *f*-test to determine whether a single regression is more efficient than two separate regressions involving splitting the data into two sub-samples. This could occur as follows, where in the second case we have a structural break at time *t*:

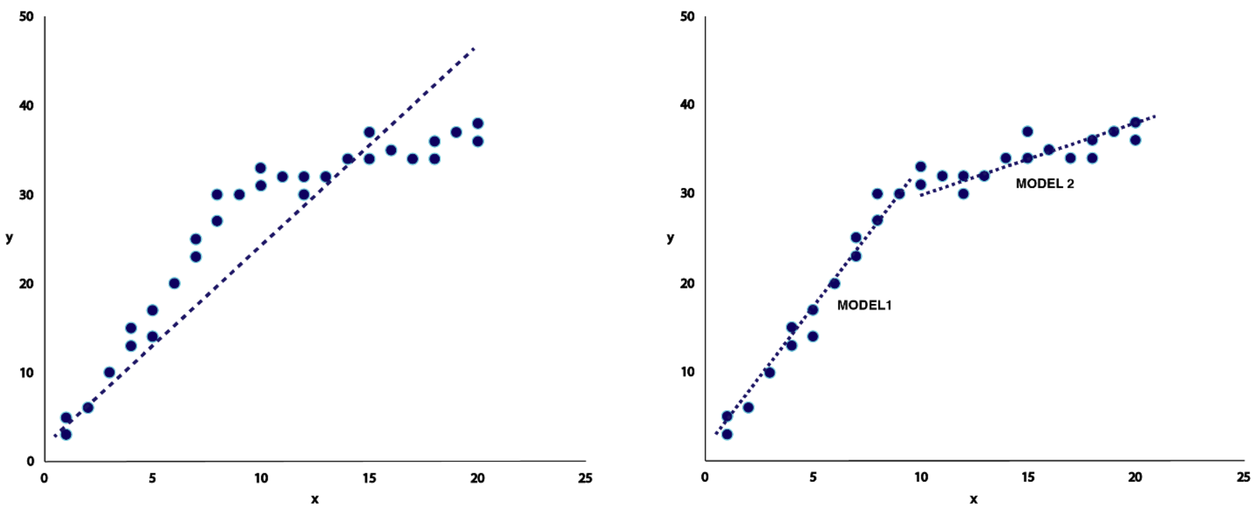

Figure 5.11: Restricted (Left: Case 1) versus unrestricted models (Right: Case 2)

In the first case we have just a single regression line to fit the data points (scatterplot), it can be expressed as:

$$y_t = \alpha_0 + \alpha_1 x_t + u_t \tag{5.15}$$

In the second case, where there is a structural break, we have two separate models, expressed as:

$$y_t = \beta_1 + \beta_2 x_t + u_{1t}$$
$$y_t = \delta_1 + \delta_2 x_t + u_{2t}$$

For the Chow test, there is a need to create an interaction term (*breakx*) of the regressor, Cumulative Installed Capacity, and the dummy variable, *break*. With this done, a regression model with the interaction and the dummy variables are fitted accordingly. The coefficient of *breakx* is the deviation of the validation period intercept from the training period intercept (break=0).

This suggests that model 1 applies before the break at time *t*, then model 2 applies after the structural break. If the parameters in the above models are the same, i.e. $\beta_1 = \delta_1$, $\beta_2 = \delta_2$, then models 1 and 2 can be expressed as a single model as in case 1, where there is a single regression line.

Chow test can be performed by running the regression using all the data, before and after the structural break, collect RSS_c. This is followed by two separate regressions on the data before and after the structural break, collecting the RSS in both cases, giving RSS_1 and RSS_2.

Using these three values, calculate the test statistic from the following formula:

$$F - \frac{RSS_c - (RSS_1 + RSS_2)/k}{RSS_1 + RSS_2 / n - 2k} \tag{5.16}$$

The resulted *f*-test should provide the critical values in the *f*-test tables, which is in this case it has F(k, n-2k) degrees of freedom. In most of the cases, this formula is strictly calculated using statistical software packages, and not manually. With this done, a conclusion can be made whether to accept or reject the null hypothesis of the test as follows:

H_0: There is no structural breaks

H_1: There is a structural break at a certain point in time

It is worth mentioning that the Chow test should only be used when the possible structural break is at a *known* time. In other words, the test shouldn't be used repeatedly to determine if any point in time can be considered a structural break.

5.9 Conclusion

In this chapter, the focus was on methods to evaluate predictions, for many reasons. First, the goal of the model is to "predict". Second, if a model can't even predict well, it's hard to see how it could be right scientifically. Third, one of the best ways of checking a scientific model is to turn some of its implications into statistical predictions.

In the forecasting literature, it is an established fact that no single forecasting model is the best for all situations under all circumstances (Makridakis et al., 1982). Therefore, the ''best' model in most real-world forecasting situations should be the one that is robust and accurate for a long-time horizon and thus users can have confidence to use the model repeatedly.

This chapter explained how the proposed models will be applied to the data in this study, which methods will be used to compare them, the data analysed in this research, and limitations in the data that will need to be addressed.

If the hypotheses are supported and diminishing learning effects are found to be significant, then this research can provide a valuable proxy into future research and application of solar PV cost estimation models. It may contribute to the emerging technologies cost estimating communities understanding by: first, developing a cost modeling tool that incorporates a plateauing factor into experience curve models. Second, refining the methodology of the estimation process so that it can be used in other areas of climate change technologies for the benefit of not only the energy industry, but the public at large.

Theoretically, it appears that the nonlinear modeling is a viable alternative to the constant linear and other conventional forecasting models in forecasting technological substitutions. Hence, an appropriate scientific methodology is what evaluates the performance of both linear and nonlinear models, using the data at hand to select the best model for forecasting purposes based on the results displayed in Chapter Six.

Chapter Six: Results and Analysis

6.1 Chapter Overview

Chapter six highlights the results from the methodology and tests described in the previous chapter. Using Wright, Gompertz and the Logistic experience models results, this chapter attempts to answer the questions presented earlier in the research: first, how does the incorporation of the saturation level impact the accuracy of solar PV modules cost estimates? Second, at what point does Wright's experience curve become less accurate in reflecting costs compared to other experience models? And third, will using contemporary nonlinear models reduce forecast error compared to the conventional estimation models?

The parameters of these models were estimated by Least Squares Estimation function (Ordinary Least Squares (OLS) and Nonlinear Least Squares (NLS)). The chapter also shows the results of the research hypotheses testing performed to complete the models' comparison.

Comparison is based on the resulted *p*-values of parameters, adjusted R-squared, SSE (Sum of Squared Error), RMSE (root mean square error), MAE (mean absolute error), MAPE (Mean Absolute Percent Error). Stata statistical software package was used to estimate the model and perform the post-hoc analysis.

The following graphs and charts illustrate and explain how the procedure, that was previously laid out, was used to complete this analysis. It was conducted on a period of 25 years (ranging between 1997 and 2021) of global silicon-based solar PV modules cumulative installed capacity and prices data points, while forecasts were made into the future until 2030. The focus of this chapter is on displaying the results only. Further analysis, conclusions, limitations, and the implications of this research will be discussed in chapter seven.

6.2 Data Description and Analysis

Historical time series dataset was analysed and refined as described in Chapter Five. The data includes global prices of silicon-based solar PV modules measured in $/W, and cumulative solar PV installed capacity measured in MW. It avoids high uncertainty of the data prior 1996 for the reasons explained in Chapter Five.[43] Despite fluctuations in the market, the curves tend to look like smooth curves on the long-term. These holds correct for the cumulative installed capacity line as seen in Figure 6.1. However, the price line, even on the long-term, is less smooth. The graph plot shows fluctuations in prices over the estimation period. It also shows that cost reduction curve is getting slow, slower than the installed capacity curve, towards the end of the production cycle. Prices are not falling, as fast as they previously did, after a certain point in time regardless of the installed capacity size.

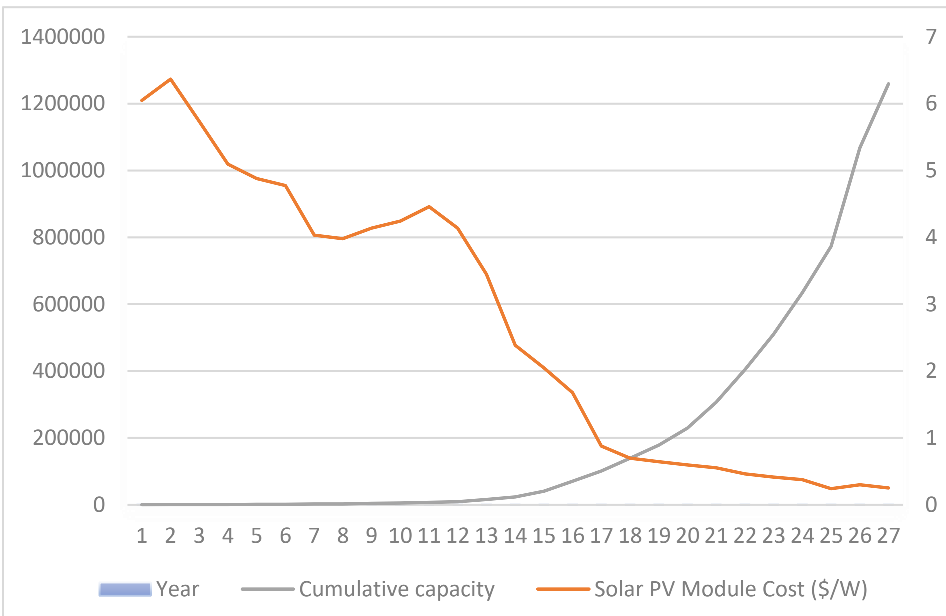

Figure 6.1: Cumulative installed capacity (MW) and module cost ($/W) against time

43 Sources of data are listed in Appendix 1

In 2020, high shipping prices, due to the COVID-19 pandemic and lockdown in many countries, put pressure on the solar PV industry growth expectations and caused a bottleneck in the raw materials supply chain. The consequences were, in return, a reverse in the modules prices curve after many years of gains in the industry. An earlier example on a reverse in the price curve is seen on the chart during the silicon shortage crisis between 2004 and 2009, which resulted in a sharp increase in silicon-based modules' prices as described in Chapter Three.

6.2.1 Inflation-Adjusted Costs

Figure 6.2 highlights the result of the price inflation-adjustment procedure that was applied on the original prices dataset. By plotting the original prices data and inflation-adjusted prices along with installed capacity against years, the difference became obvious between the two lines. Beyond this point, inflation-adjusted price data was used throughout this analysis to ensure more reliable results.

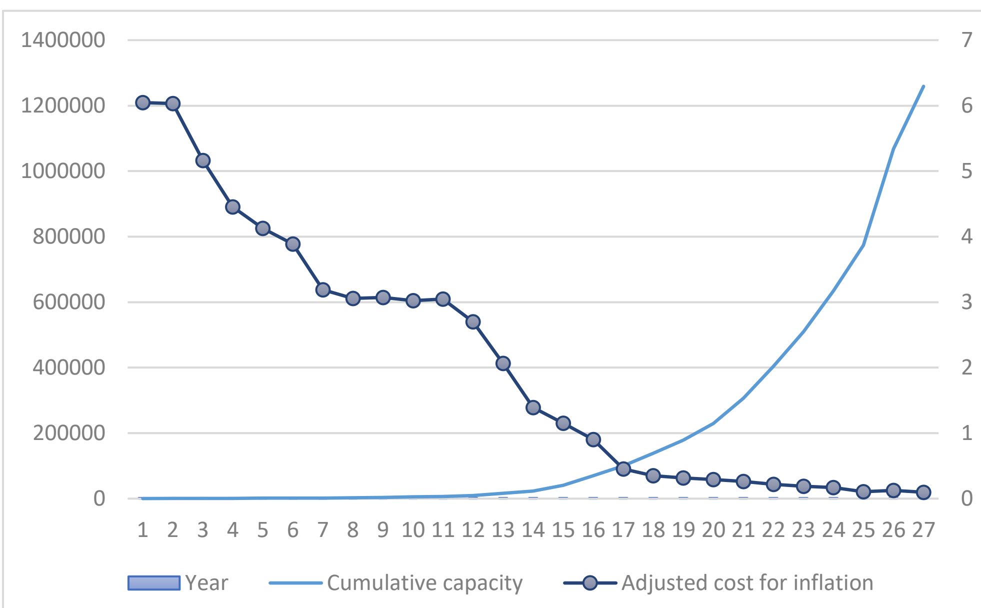

Figure 6.2: Inflation-adjusted module price ($/W) versus cumulative capacity (MW) over years

6.2.2 Log Transformation

After adjusting prices for inflation, the dataset was tested for a potential trend or skewness. High skewness was detected using boxplots (see Figure 6.3 and 6.4 below) and in the data summary, shown in Table 6.1:

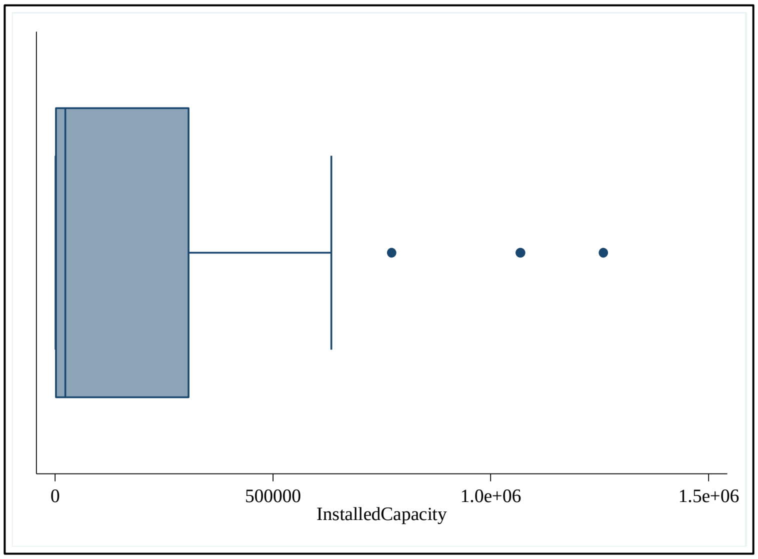

Figure 6.3: Cumulative Capacity Boxplot

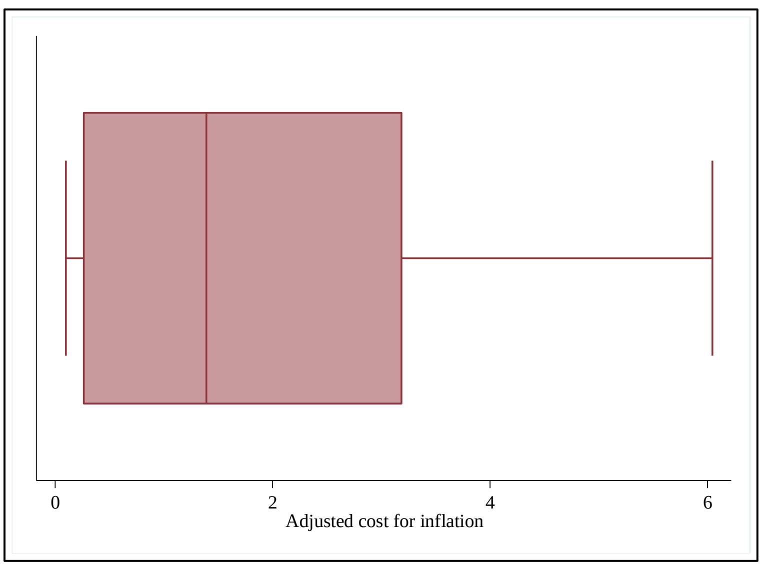

Figure 6.4: Inflation-Adjusted Cost Boxplot

	Inflation-Adjusted Cost ($/W)	Installed Capacity (MW)
Mean	2.07	214,253.30
Standard Deviation	1.96	346,632
Variance	3.83	1.20E+11
Skewness	0.61	1.79
Kurtosis	2.13	5.22

Table 6.1: Detailed summary on inflation-adjusted cost and cumulative installed capacity variables

The ideal value to aim for in regard to the skewness is zero. If skewness is less than -1 or greater than 1, the distribution is highly skewed. If skewness is between -1 and -0.5 or between 0.5 and 1, the distribution is moderately skewed. If skewness is between -0.5 and 0.5, the distribution is approximately symmetric.

The solution for the skewness, as suggested in Chapter Five, was to transform the data. Log transformation is recommended for both the dependent and the independent variables. Both log-transformed variables will be used throughout this analysis. As discussed, log-transformation is also applied to remove any potential presence of unit-root as well.

The new introduced variables are *LnModuleCost* and *LnInstalledCapacity* which are the natural logarithms for *ModuleCost* and *InstalledCapacity* variables respectively. Based on this criterion, the improvement in the data is confirmed graphically for log-transformed variables in Figure 6.5 boxplot and in Table 6.2 below:

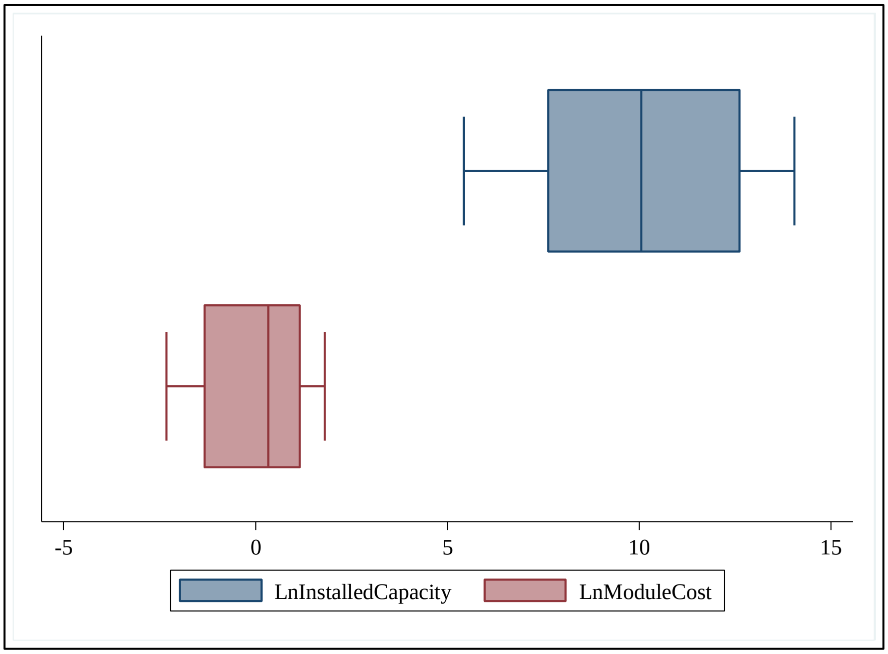

Figure 6.5: Log-transformed data boxplots

	LnInflation-Adjusted Cost ($/W)	LnvInstalled Capacity (MW)
Mean	0.01	10.03
Standard Deviation	1.42	2.78
Variance	2.02	7.71
Skewness	-0.29	-0.14
Kurtosis	1.51	1.69

Table 6.2: Detailed summary on log-transformed cost and capacity variables

6.2.3 Dataset Splitting

The dataset was split into two subsets: training, validating. There is no rule of thumb on how to split the dataset, yet it requires deep understanding to the data and the problem being solved. Typically, most researchers go with the 80/20 rule; which means 80 percent of the data points are used to train (estimate) the model, and 20 percent is used to validate the results. In this research, nonlinear models are estimated which means data points are needed to ensure a successful convergence and iteration of the model. Therefore, 81% of the data was used to train the model, and 19% was used to validate the model as shown in Table 6.3. Finally, data for forecast (testing) is collected from Bloomberg New Energy Finance (BNEF) future forecasts on cumulative installed capacity (MW) to establish future scenarios using various estimated models:

Training data	1996-2017	22 years/ data points
Validation data	2018-2022	5 years/ data points
Testing data	2023-2030	8 years/ data points

Table 6.3: Data Splitting Structure

6.3 Regression Analysis Results:

6.3.1 Ordinary Least Squares (OLS) Estimation Result

Using the Ordinary Least Squares (OLS) technique, Wright's power law regression resulted in Table 6.4:

Source	SS	df	MS
Model	25.2821559	1	25.2821559
Residual	1.98083661	20	.09904183
Total	27.2629926	21	1.29823774

Number of obs	=	22
F(1, 20)	=	255.27
Prob > F	=	0.0000
R-squared	=	0.9273
Adj R-squared	=	0.9237
Root MSE	=	.31471

LnModuleCost	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LnInstalledCapacity	-.4552378	.0284932	-15.98	0.000	-.5146735	-.3958021
_cons	4.658695	.2712279	17.18	0.000	4.092924	5.224467

Table 6.4: The ANOVA table for the OLS Wright regression model

Table 6.4 contains the result of the OLS estimation which includes the ANOVA table as expected, the R^2 value and the Mean Squared Error (MSE) values. Results of the coefficients estimation are significant (with *p*-values less than 0.05 at the 95% confidence level and $\alpha = 5\%$) in the ANOVA table, and high R^2, which gives a statistically significant starting point to analyse the result.

a. Fitted Values, Coefficients and Goodness-of-fit

The OLS estimation of Wright's power law model resulted in 0.9273 and a slightly lower adjusted R^2 value of 0.9237 using the training dataset. This means that approximately 92% variance in the dependent variable (inflation-adjusted prices) can be explained by the independent variable (cumulative installed capacity) in the estimated model.

The estimated learning coefficient, *b*, named LnInstalledCapacity in the ANOVA table, is the slope of the linear regression model (-0.455). In the experience curve analysis context, the importance of this value is in its role in calculating the progress ratio and, consequently, the learning rate of the experience curve model. According to Wright's model, the cost is reduced by *b%* every time the production capacity doubles. The result of this calculation provides the progress ratio of the model as follows:

Progress Ratio (PR) = $2^{-b} = 2^{-0.455} = 0.73$ (6.1)

Learning Rate = 1 – PR = 1 – 0.73 = 0.27 = 27% (6.2)

Using these equations, Wright's model estimated a 27% constant learning rate over time. Also, the inverse relationship between the progress ratio and the learning rate is observed. The higher the progress ratio, the lower the learning rate of the model, and vice versa.

The intercept of the linear regression model, named (*_cons*) in the ANOVA table, is the natural log of the theoretical first unit, Y_1 value. This is calculated by raising the mathematical constant e to the estimated value of the intercept which in this case is 4.65 as follows:

Cost of first unit (\$) = $e^{\text{intercept}} = e^{4.65}$ = \$104.6 (6.3)

Estimated coefficients are used as the new inputs of the model to predict solar PV modules prices based on the trained model. Predictions are made for both the training data subset (observations 1 to 22) and the validation subset (observations 23 to 27) to understand how the model performed as shown in Figure 6.6:

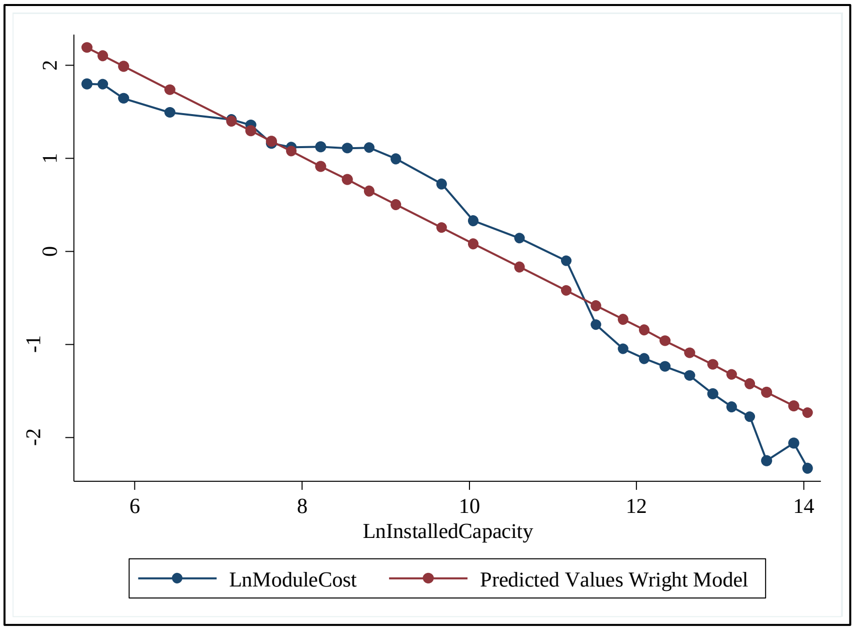

Figure 6.6: Actual prices versus predicted prices ($/W), Wright's Model

b. Standard Error of the Regression: Model and Error's Assumptions

Once predicted data is obtained, residuals of the model are calculated by measuring the distance between predicted values of y (dependent variable) and observed values of y:

$$Residuals_i = actual\ y_i\ value - predicted\ y_i\ value \tag{6.4}$$

Using the results from equation (6.4), it is critical to check that all model's assumptions explained in Chapter Five, are met, and satisfied correctly. This step helps to achieve reliable outcomes from the model. Accordingly, it is also important to fix any violation of these assumptions if found. An array of graphical and statistical tests were performed on the residuals as follows:

1. **Linearity:** the equation used for this analysis is linear in the parameters as estimated by the Ordinary Least Squares (OLS) method. Linearity between the dependent variable, *LnModuleCost*, and the independent variable, *LnInstalledCapacity*, is confirmed graphically in Figure 6.7:

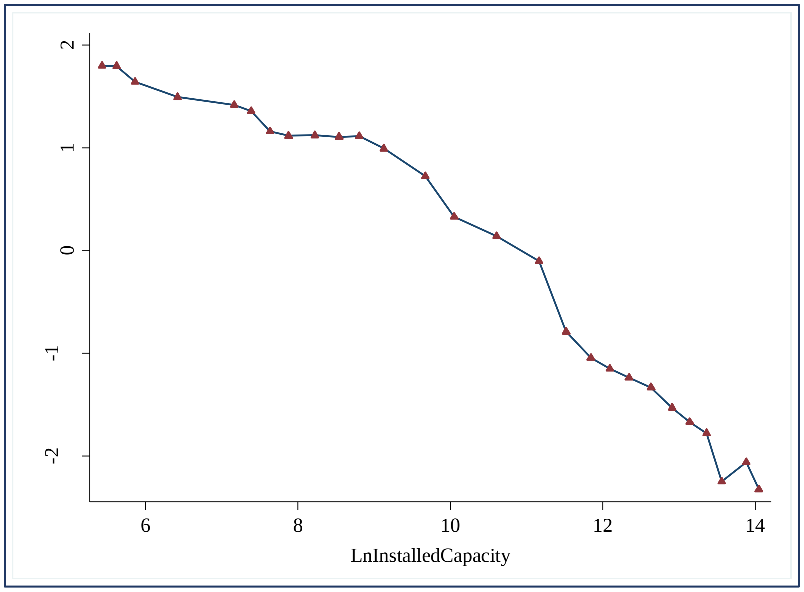

Figure 6.7: Relationship between the dependent and the independent variables

2. **Independence of errors (No-Autocorrelation):** this assumption is statistically examined using the well-known Breusch-Godfrey test for autocorrelation. The null hypothesis (H_0) indicates that there is no serial correlation, while the alternative hypothesis (H_1) indicates that residuals are serially correlated. In real life, most software packages offer this test after the Ordinary Least Squares (OLS) model estimate. As for the estimated model, the Breusch-Godfrey test result is as shown in Table 6.5:

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	15.315	1	0.0001

H0: no serial correlation

Table 6.5: Breusch-Godfrey statistics result

The results above indicate a p-value of 0.0001 which is significant and provides enough evidence to reject the null hypothesis that there is no serial correlation. This means that there is a serial correlation (autocorrelation) in the model's errors. One more confirmation is given through the Durbin-Watson (DW) test for autocorrelation. The statistic of the Durbin-Watson test is (*0.25*) which is much lower than (2): the level where no-autocorrelation can be assumed. Graphically, autocorrelation can be seen as follows in Figure 6.8 and Figure 6.9:

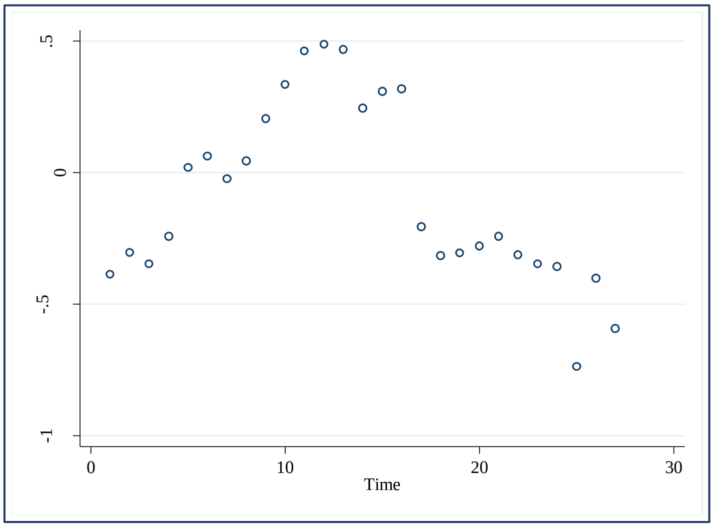

Figure 6.8: A plot for Residuals versus Time

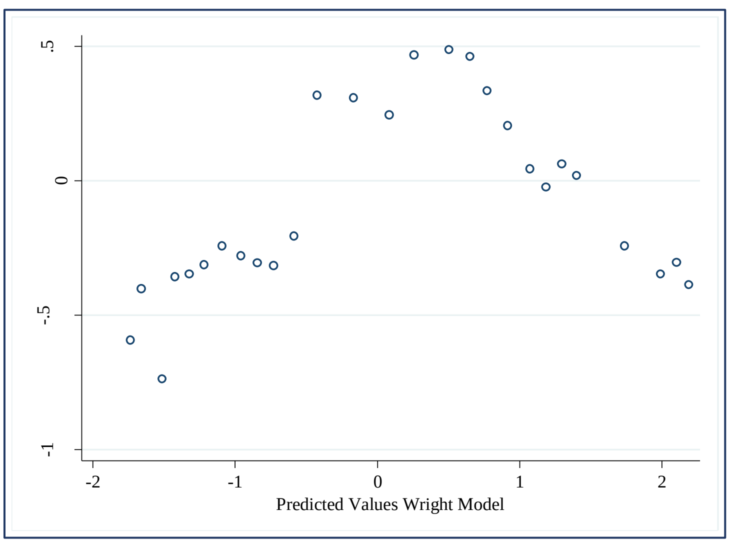

Figure 6.9: A plot for residuals versus Predicted Values

Despite being popular in time-series analysis, Autocorrelation is still a worry and can affect the model's reliability. Therefore, another step was taken to solve this issue. As explained in detail in Chapter Five, the Newey-West (NW) test is among the frequently used methods to correct for autocorrelation where the original model can be retained.

This estimate works to have more precise confidence intervals for the estimated coefficients to account for autocorrelation and heteroscedasticity. The newly specified confidence intervals on the estimated coefficients (lag = 1) are displayed in Table 6.6:

```
Regression with Newey-West standard errors      Number of obs     =         22
maximum lag: 1                                  F(  1,        20) =     157.58
                                                Prob > F          =     0.0000
```

LnModuleCost	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
LnInstalledCapacity	-.4552378	.0362645	-12.55	0.000	-.5308842	-.3795914
_cons	4.658695	.3430509	13.58	0.000	3.943104	5.374287

Table 6.6: Newey-West regression result

Outcomes from the Newey-West test were as follows: the *p*-value of the *f*-test is significant which means the estimation of updated confidence intervals of estimated coefficients is statistically significant at the 95% confidence level ($\alpha = 5\%$). However, confidence intervals are narrower from the original models which is expected as a result of the Newey-West regression.

3. **Normality:** Normality in residuals is recommended, but not compulsory. It is checked using a statistical estimate using Shapiro-Wilk test for normality, and graphically through Histograms which measure the deviation of the residuals from the normal density. As for the Shapiro-Wilk test, the null hypothesis of the test (H_0) is that data are normally distributed, while the alternative hypothesis (H_1) indicates that data are not normally distributed. The result of the test came back as seen in Table 6.7:

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
Residuals	27	0.92670	2.155	1.577	0.05738

Table 6.7: Shapiro-Wilk test for normality in the residuals (Wright Model)

As seen above, at the 95% confidence level, the test result didn't provide enough evidence to reject the null hypothesis. The resulted *p*-value is slightly higher than the significance level 0.05 ($\alpha = 0.05$). Therefore, the null hypothesis is accepted that the residuals are normally distributed. Next, a histogram was built on the residuals which showed an approximately normally distributed residuals as in Figure 6.10:

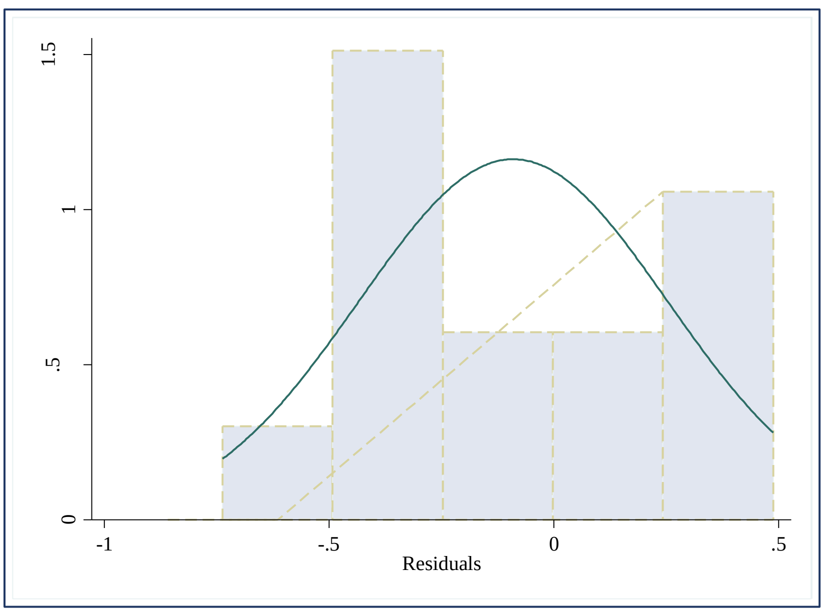

Figure 6.10: Residuals versus time Histogram

4. Equality of Variance (Homoscedasticity): Using Newey-West test to correct for autocorrelation, this model also accounts for and is robust to heteroskedasticity (unequal variance of the residuals). Accordingly, the equality of variance assumption can be assumed as a satisfied assumption.

6.3.2 Nonlinear Least Squares (NLS) Estimation Result: Gompertz and the Logistic Model

Gompertz Model:

As for *Gompertz model*, non-linear least squares (NLS) technique is used to estimate the model's parameters. Using the interactive version of the nonlinear least squares techniques in modern software packages, the nonlinear least squares method became a more user-friendly function that was directly applied to the Gompertz equation to estimate the model's parameters as shown in Table 6.8:

Source	SS	df	MS
Model	26.942841	3	8.98094684
Residual	.32015203	18	.017786224
Total	27.262993	21	1.29823774

Number of obs	=	22
R-squared	=	0.9883
Adj R-squared	=	0.9863
Root MSE	=	.133365
Res. dev.	=	-30.62674

4-parameter Gompertz function, LnModuleCost = b0 + b1*exp(-exp(-b2*(LnInstalledCapacity - b3)))

LnModuleCost	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b0	-1.991	.4211003	-4.73	0.000	-2.875699	-1.106301
/b1	3.781151	.505241	7.48	0.000	2.719679	4.842623
/b2	-.5491614	.0834467	-6.58	0.000	-.7244765	-.3738464
/b3	11.47631	.3733145	30.74	0.000	10.692	12.26061

Parameter b0 taken as constant term in model & ANOVA table

Table 6.8: Gompertz Nonlinear Least Squares (NLS) Estimate Results

a. Fitted Values, Coefficients and Goodness-of-fit

The Goodness-of-fit, R^2, value is high with 0.9883 and 0.9863 in the Adjusted R-squared. It means that 98.6% variance in the dependent variable (inflation-adjusted prices) can be explained by the independent variable (cumulative installed capacity) in the estimated model. However, this significant result might be a sign of overfitting in the model as discussed in Chapter Seven.

The R^2 value is for the evaluation and understanding of Gompertz model only. Due to the different number of parameters between linear and nonlinear models, it is not possible to use this value for model comparison later in Chapter Seven. However, it will be compared with the R^2 value for the following 4-parameter Logistic model.

Estimated coefficients have different meanings from conventional linear models. The constant parameter, b_0, is -1.9 which was basically added to improve the model's specification, and to allow for a smooth and successful convergence in the model given the small sample size. The second parameter, $b_{1,}$ with 3.78 value is the maximum capacity. Parameter $b_{2,}$ is the initial rate of growth at -0.54. The upper asymptote, $b_{3,}$ 11.47 is the slope factor of the model. The Gompertz model is a double-exponential asymmetrical model, which means the inflection point doesn't happen exactly half-way the curve, and the flattening of the curve is expected to take place faster.

Those parameters are used to predict solar PV modules prices based on the estimated model. Predictions are made for both the training period and the validation period to understand how well the model performed as shown in Figure 6.11:

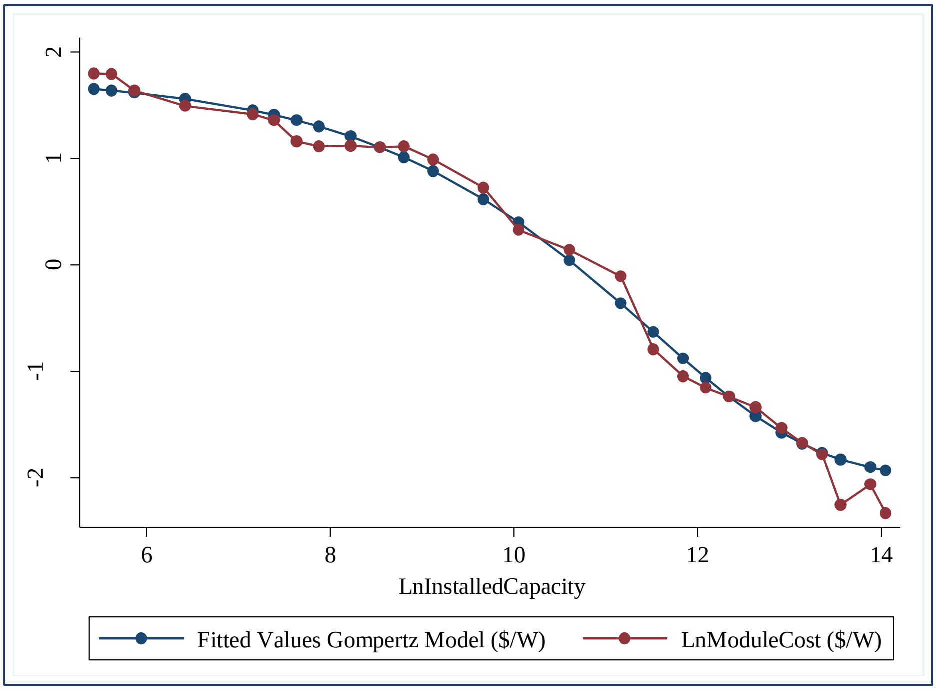

Figure 6.11: Gompertz Model Predicted modules prices versus actual prices $/W

b. Standard Error of the Regression: Model and Error's Assumptions

Once predicted data is obtained, residuals of Gompertz model are calculated using the same equation for residuals, Equation 6.4 ($Residuals_i = actual\ y_i\ value - predicted\ y_i\ value$).

Regarding the calculated errors, it is critical to check that all nonlinear regression model and error's assumptions explained in Chapter Five, are met and satisfied correctly to ensure the robustness of the model. It is also important to fix any violation of these assumptions if found. A number of graphical and statistical tests was performed on the residuals as follows:

1. The model fits the data well: the estimated model results show good harmony between the model's function and the data used to estimate the model.
2. Normality: as discussed for linear models, Normality in residuals is recommended, but not compulsory. It is, however, checked through the Shapiro-Wilk test, and graphically through Histograms. Shapiro-Wilk test result was as follows in Table 6.9:

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
Residuals	27	0.95329	1.373	0.651	0.25740

Table 6.9: Shapiro-Wilk test for normality in Gompertz model residuals

The resulted *p*-value of Shapiro-Wilk test is not significant (*p*-value = 0.25), which doesn't provide enough evidence to reject the null hypothesis (H_0) that residuals are normally distributed. A histogram was plotted of the residuals which confirmed the Shapiro-Wilk test result of normally distributed residuals as seen in Figure 6.12:

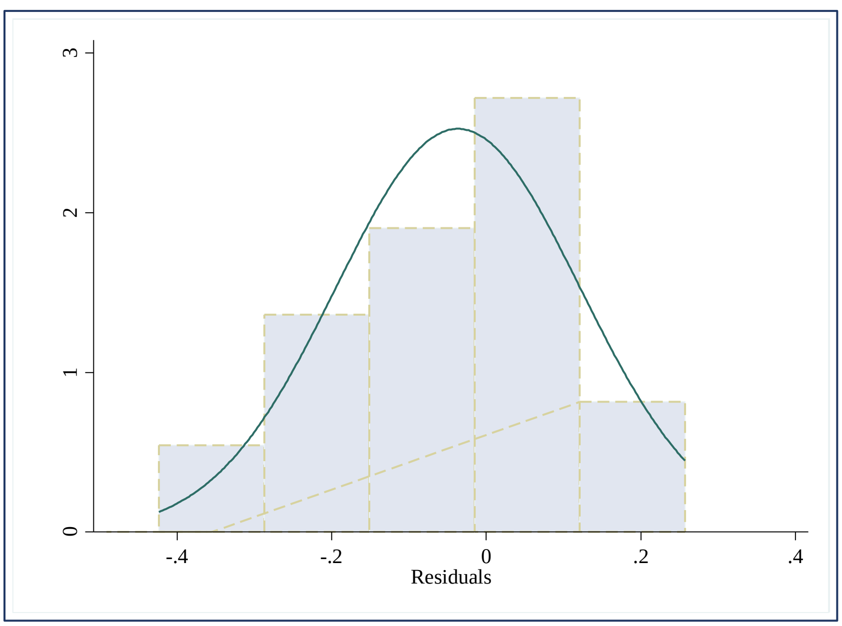

Figure 6.12: Histogram: Residuals versus time

Therefore, and according to Shapiro-Wilk test and the plotted histogram, residuals are normally distributed as recommended.

3. Variances are homogeneous: plotting the residuals against time confirms that errors of the Gompertz model are homogenous, scattered randomly around the zero line with few outliers, as seen in Figure 6.13:

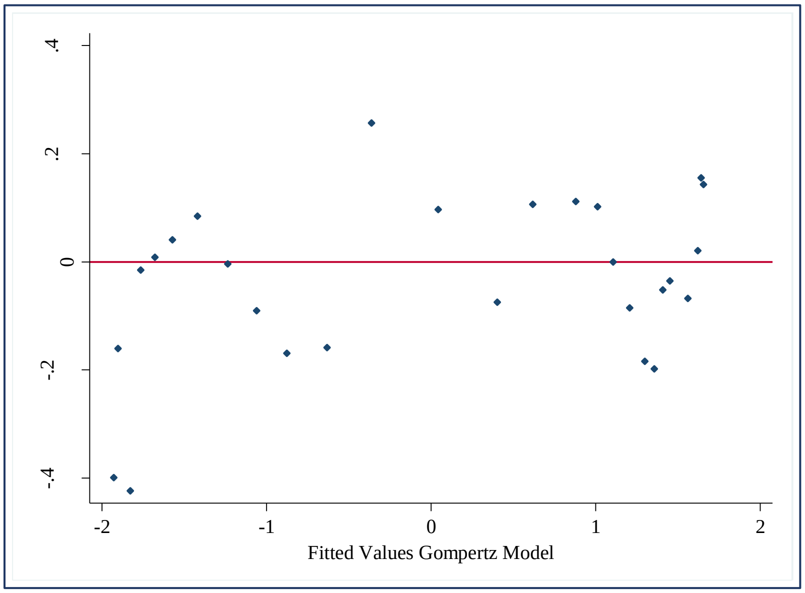

Figure 6.13: Predicted values versus residuals around the zero line

The Logistic Model:

The non-linear least squares (NLS) technique is used to estimate the Logistic model parameters. Using the same version of the nonlinear least squares (NLS) technique in statistical software packages, the nonlinear least squares method was directly applied to the Logistic equation using the training dataset, to compute the regression results shown in Table 6.10:

Source	SS	df	MS
Model	26.917841	3	8.97261353
Residual	.34515197	18	.019175109
Total	27.262993	21	1.29823774

Number of obs	=	22
R-squared	=	0.9873
Adj R-squared	=	0.9852
Root MSE	=	.1384742
Res. dev.	=	-28.97259

4-parameter logistic function, LnModuleCost = b0 + b1/(1 + exp(-b2*(LnInstalledCapacity - b3)))

LnModuleCost	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b0	-3.36151	1.184632	-2.84	0.011	-5.850331	-.87269
/b1	5.156406	1.291738	3.99	0.001	2.442565	7.870247
/b2	-.5775522	.1236991	-4.67	0.000	-.8374343	-.31767
/b3	11.75085	.7807123	15.05	0.000	10.11063	13.39107

Parameter b0 taken as constant term in model & ANOVA table

Table 6.10: The Logistic Nonlinear Least Squares (NLS) Estimate Results

a. Fitted Values, Coefficients and Goodness-of-fit

The Goodness-of-fit, R^2, value is very high with 0.9873 and 0.9852 in the Adjusted R-squared. It means that 98.5% variance in the dependent variable (inflation-adjusted prices) can be explained by the independent variable (cumulative installed capacity) in the estimated model using 22 data points (the training period). Potential overfitting, based on this result, will be discussed in chapter seven.

The R^2 value is also for the evaluation and understanding of Logisitc model, and for comparison with Gompertz 4-parameter model only. Due to the different number of parameters between linear and nonlinear models, this value is not used for model comparison with Wright's model.

As stated earlier, estimated coefficients have different meanings from conventional linear models. The constant parameter, b_0, is -3.36. This constant parameter helps to improve the model's specification, and to allow for a smooth and successful convergence in the model. The second parameter, b_1, with 5.15 value is the maximum capacity. Parameter b_2, is the initial rate of growth at -0.577. The upper asymptote, b_3, 11.75 is where the model reaches its maximum value and starts to decay.

The Logistic model is a symmetrical model, which means the inflection point occurs exactly half-way the curve. The curve also converges linearly towards the zero which makes it slower than the double exponential Gompertz curve.

The estimated parameters are used to predict solar PV modules prices and compare it to actual values. Predictions are made for both the training data subset and the validation subset to understand how well the model performed as shown in Figure 6.14:

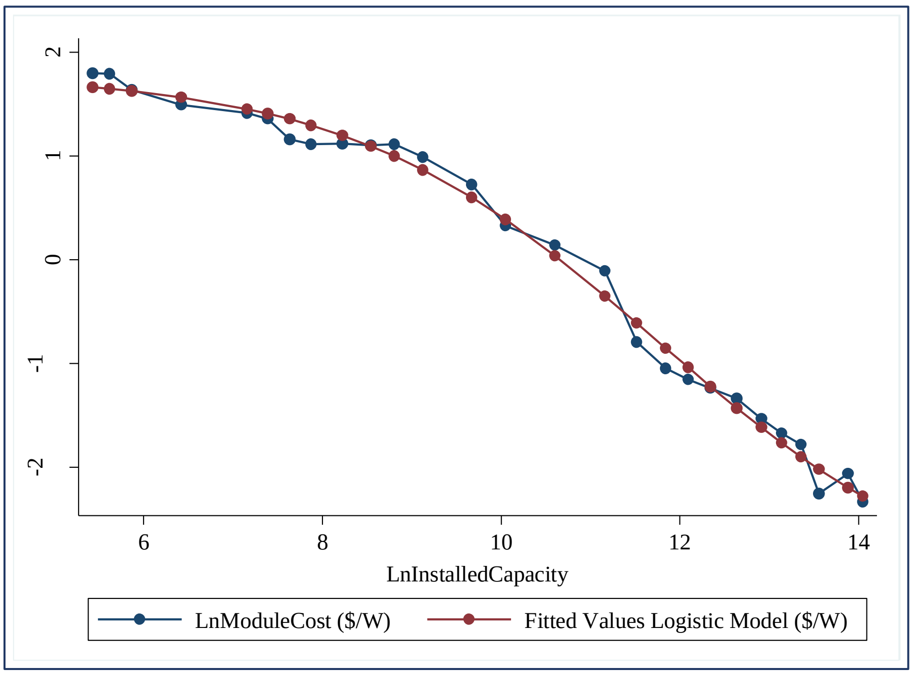

Figure 6.14: Predicted prices versus actual prices $/W

b. Standard Error of the Regression: Model's Assumptions

Once predicted data is obtained, residuals of the Logistic regression are calculated by measuring the distance between each point and the graph using Equation 6.4. Regarding the fitted model and the calculated errors, it is important to check that all nonlinear regression model's assumptions explained in Chapter Five, are met and satisfied correctly, and fix any violation of these assumptions if found. Assumptions of the model were checked as follows:

1. The model fits the data well: the Logistic model shows reasonable fit between the model's function and the data used to estimate the model's parameters using the NLS technique.
2. Normality: as discussed for previous models, Normality in residuals is recommended, but not compulsory. It is again checked graphically through Histograms and by running the Shapiro-Wilk test for normality as follows in Table 6.11:

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
Residuals	27	0.93681	1.858	1.272	0.10164

Table 6.11: Shapiro-Wilk test for normality result

The resulted *p*-value of Shapiro-Wilk test is significant (*p*-value = 0.10) which does not provide enough evidence to reject the null hypothesis (H_0) that residuals are normally distributed. A histogram was plotted on the residuals which confirmed the Shapiro-Wilk test result:

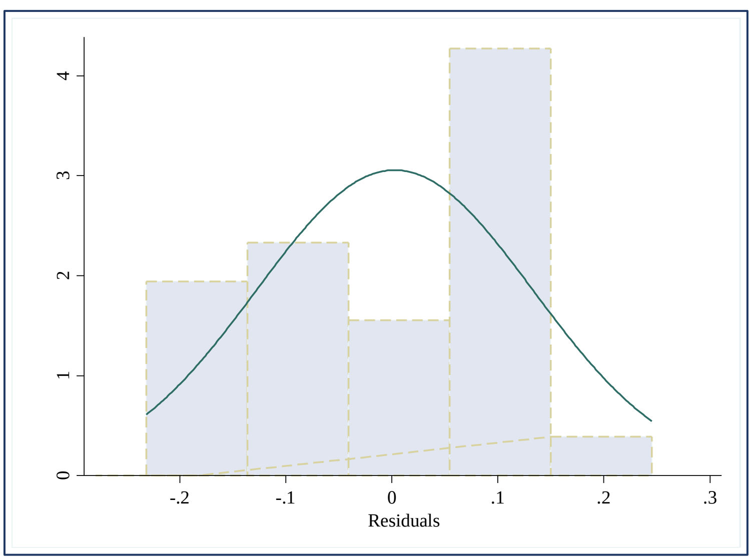

Figure 6.15: Histogram: Residuals versus time

According to Shapiro-Wilk test and the plotted histogram, residuals are normally distributed.

3. Variances are homogeneous: plotting the residuals against time confirms that errors of the Logistic model are homogenous, scattered randomly around the zero line, yet with few outliers as seen in Figure 6.16:

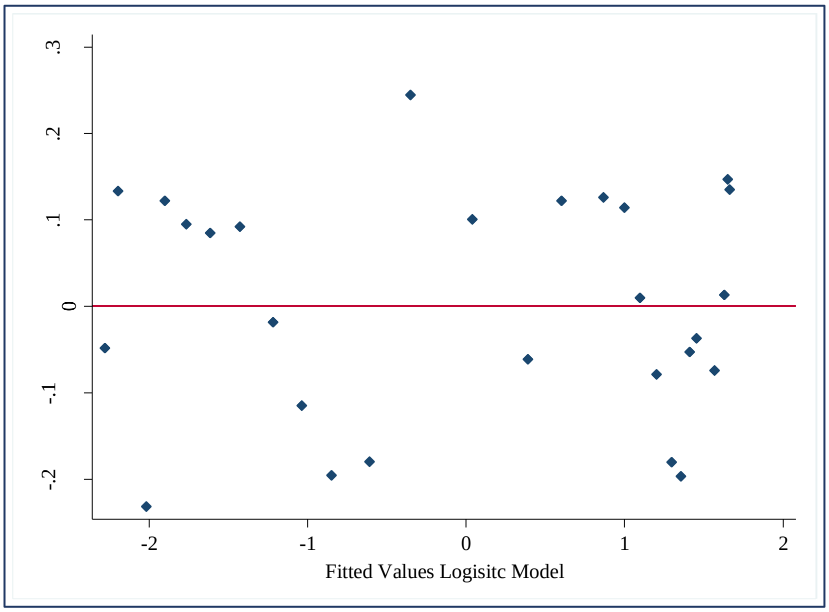

Figure 6.16: Predicted values versus residuals around the zero line

6.4 Forecast Errors

There are many available metrics to evaluate the performance of the estimated models, which indicates the need for a strategy on how to perform the model's evaluation. It is however recommended to use more than one evaluation method, which gives more confidence in the robustness of the estimated model. Empirical results have demonstrated that using such a mix of error measures instead of just one leads to overall better, robust and generalisable results even when the final evaluation is performed with just one of those measures. As mentioned before, residuals of the model is calculated using the simple equation of:

$$e_t = y_t - \hat{y}_t$$

where:

e is the calculated error, y_t is the actual value of y at time t, and $\hat{y}_t$ is the predicted value of y_t at time t.

Using calculated errors for each model (Wright, Gompertz and the Logistic), certain measures are considered for models' evaluation. What is needed is to populate the error's values in a table, calculate the squared error, the absolute value of the error, and the Absolute Percent Error (APE); the absolute value of the error at time t, divided by the actual cost during t for each model.

6.4.1 Scale-dependent Errors

The resulted values of the scale-dependent errors (Sum of Squared Error (SSE), Mean Absolute Error (MAE), Mean Absolute Error (MSE), and the Root Mean Squared Error (RMSE)) for the training and the validation periods are summarised in Table 6.12 as follows:

	Training Dataset				Validation Dataset			
	SSE	MAE	MSE	RMSE	SSE	MAE	MSE	RMSE
Gompertz	0.32	10.18	1.46	1.21	0.36	20.13	7.30	2.70
Logistic	0.35	10.83	0.73	0.85	0.10	12.63	1.96	1.40
Wright	1.98	26.91	9.00	3.00	1.30	48.68	26.05	5.10

Table 6.12: Values of Scale-dependent Error measurements

6.4.2 Percentage Errors

For both the training and the validation, the unit-free Mean Absolute Percent Error (MAPE) calculated using the previously mentioned equation in Chapter Five, and results came out as follows in Table 6.13:

	Training Dataset (%MAPE)	Validation Dataset (%MAPE)
Gompertz	22.53	9.02
Logistic	22.67	6.29
Wright	47.03	23.69

Table 6.13: Values of Percent Error measurements

6.5 Research Hypotheses Testing

Following the methodology stated in Chapter Five, statistical tests were performed to test the following research hypotheses:

H_1: One or more of the three experience curve models has a MAPE significantly different from the other models.

H_2: One or more of the alternative experience curve models is significantly more accurate than Wright's model in predicting solar PV modules costs.

H_3: The nonlinear model, which accounts for both previous experience and the plateauing effect, has the lowest MAPE, being the most accurate predictor of solar PV modules costs.

As for **the first hypothesis**, there was a need to test whether it was possible to use a parametric test to compare the mean of the absolute percent error between the three models. Parametric one-way ANOVA test requires three conditions to be met for valid results: the samples must be randomly selected from the population; the samples have distributions that are approximately normal, and the population variances must be equal (McClave, Benson, Sincich 2011). The samples are random in the sense that there was no selection process from the data. The second condition of the parametric test is normality of the data. As for the Absolute Percent Error (APE) data for the three models, normality is checked by applying the Shapiro-Wilk test for normality, and graphically by plotting histograms for the APE values against time as follows.

The null hypothesis (H_0) of Shapiro-Wilk test for normality indicates that APE values are normally distributed. The alternative hypothesis (H_1) indicates that these values are not normally distributed. The test result came back as shown in Table 6.14:

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
WrightAPE	5	0.82319	2.087	1.157	0.12355
GompertzAPE	5	0.85716	1.686	0.778	0.21824
LogisticAPE	5	0.95640	0.515	-0.781	0.78271

Table 6.14: Shapiro-Wilk test for normality result

From Table 6.14, the resulted *p*-value for all variables is not significant and doesn't provide enough evidence to reject the null hypothesis of normally distributed variables. It is much higher than the critical value (α=0.05), therefore the null hypothesis is accepted.

Histograms below provide another clarification on how data points are approximately normally distributed:

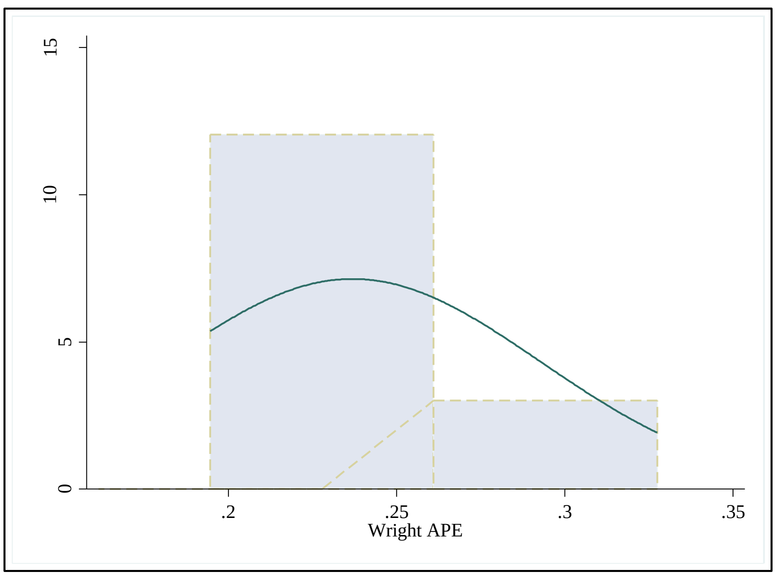

Figure 6.17: Histograms for the APE values for Wright's Model

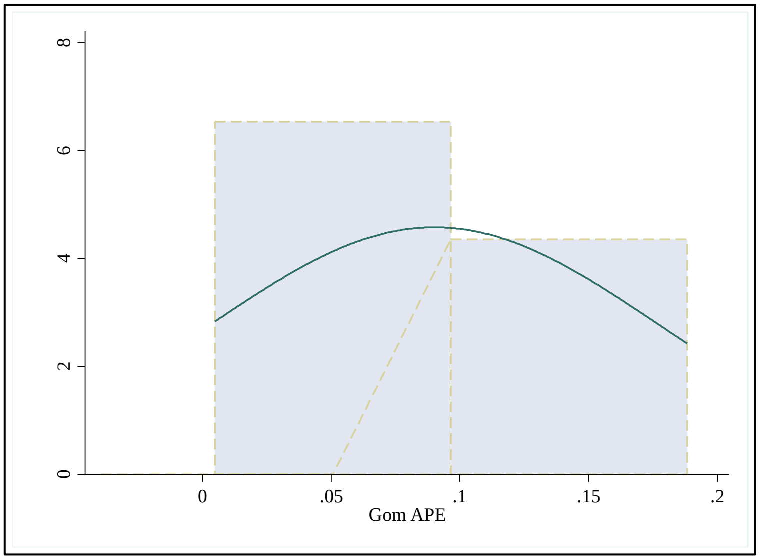

Figure 6.18: Histograms for the APE values for Gompertz Model

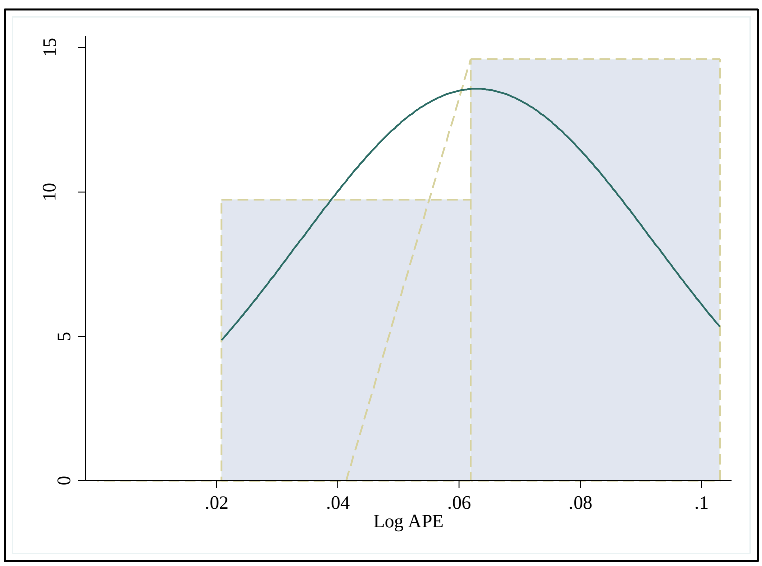

Figure 6.19: Histograms for the APE values for the Logisitc Model

Normality in the APE values is confirmed for the last time by looking at the close-to-zero skewness values for Wright, Gomopertz and the Logistic models which are 0.95, 0.13 and -0.10 respectively.

The last assumption, to determine whether a parametric or a non-parametric test should be used, is on the equality of variances. The rule of thumb for testing variance is to divide the largest sample standard deviation by the smallest. According to the descriptive statistics, Gompertz model has the largest standard deviation (0.0.87067) and the Logistic model has the smallest one (0.0293818). If the outcome value is less than four, the assumption of equal variances will be acceptable. The division's result is 2.9 with which equal variance can be assumed and one-way ANOVA test for equal means can be used.

That been said, One-Way ANOVA test was used to compare the means of the three groups in order to determine whether there is statistical evidence that the associated means are significantly different. F-test statistic will provide insight into the first hypothesis. The null hypothesis (H_0) states that all means are equal, while the alternative hypothesis (H_1) indicates that at least one group has a mean that is significantly different form other groups' means. If the F-statistic is significant, then there is enough evidence to reject the null hypothesis and at least one of the sample means is different as follows in Table 6.15:

Group	Summary of APEs Mean	Std. Dev.	Freq.
1	.23692316	.05587208	5
2	.09018904	.08706698	5
3	.06287312	.02938181	5
Total	.12999511	.09778987	15

Analysis of Variance

Source	SS	df	MS	F	Prob > F
Between groups	.087617467	2	.043808734	11.36	0.0017
Within groups	.046262559	12	.003855213		
Total	.133880026	14	.009562859		

Bartlett's test for equal variances: chi2(2) =   3.7127 Prob>chi2 = 0.156

Table 6.15: One-Way ANOVA test for means comparison

The resulted One-Way ANOVA table provided a *p*-value of 0.0017 which is less than the critical level of 5% (α=0.05) at the 95% confidence level. Therefore, the null hypothesis was rejected as there was enough evidence that at least one group has a mean that is significantly different from other groups' means. The One-Way ANOVA test was supported by the non-parametric Kruskal-Wallis test, which confirmed the same significant result at the 95% confidence level as shown in Table 6.16:

```
Kruskal-Wallis equality-of-populations rank test
```

model	Obs	Rank Sum
Gomertz	5	29.00
Logistic	5	26.00
Wright	5	65.00

```
chi-squared =     9.420 with 2 d.f.
probability =     0.0090

chi-squared with ties =     9.420 with 2 d.f.
probability =     0.0090
```

Table 6.16: Non-parametric Kruskal-Wallis equality of means rank test

The resulted *f*-statistic 0.009 is significant at the 95% confidence level (α=0.05) which confirms what the parametric ANOVA test previously found that at least one group has a mean that is significantly different from other groups' means.

As for **the second hypothesis,** the previous result paves the way to investigate if one or more of the nonlinear contemporary models is more accurate than Wright's conventional model. To perform Dunnett's test as explained in chapter five, the status quo Wright's model was held as a reference model to compare Gompertz and the Logistic models against it and determine if they are different.

Assuming equal variances, the test statistically compares Wright's model MAPE to other nonlinear models MAPE values and decide whether they are statistically different. The result of Dunnett's test is shown in Table 6.17 for both Gompertz (Group 2) and the Logistic models (Group 3) respectively, which confirms a statistical difference between the MAPE values between Wright (Group 1) and at least one of the alternative models:

```
Pairwise comparisons of means with equal variances

over         : group
```

apes	Mean	Std. Err.	Unadjusted [95% Conf.	Interval]
group				
1	.2369232	.0277677	.1764226	.2974237
2	.090189	.0277677	.0296885	.1506896
3	.0628731	.0277677	.0023726	.1233736

apes	Contrast	Std. Err.	Unadjusted t	P>|t|
group				
2 vs 1	-.1467341	.0392694	-3.74	0.003
3 vs 1	-.17405	.0392694	-4.43	0.001
3 vs 2	-.0273159	.0392694	-0.70	0.500

Table 6.17: Dunnett's test result for Gompertz and the Logistic versus Wright's model

From the above results, the *p*-value is significant for both the Logistic and Gompertz models against Wright's model (p = 0.001 and 0.003 respectively) at the 95% confidence level (α=0.05). However, Gompertz didn't show statistical difference from Wright's using this test (p = 0.50).

Based on the initial results on MAPE values in section 6.4.2 of this chapter, **the third hypothesis** was tested to determine whether one the estimated Gompertz and the Logistic experience curve models reduced the Mean Absolute Percent Error (MAPE) value significantly more than the other model. Therefore, the next step was to compare the lowest MAPE values observed in Gompertz and the Logistic models, to answer to the third hypothesis of this research on which model is the best and the most accurate forecasting model. Accordingly, a paired difference *t*-test was performed. The null hypothesis of the *t*-test (H_0) indicates that there is no significant statistical difference between the two MAPE values (for Gompertz and the Logistic models). The alternative hypothesis (H_1) indicates that there is a significant statistical difference between the two MAPE values. At 95% confidence level, if *t*-test Statistic is less than the 5% critical value ($\alpha = 0.05$), then there is enough evidence to reject the null hypothesis and conclude that one of these two models performed best as seen in Table 6.19:

```
Paired t test
------------------------------------------------------------------------------
Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
   apeh3 |      10    .0765311    .0199001    .0629296     .031514    .1215482
 modelh3 |      10         2.5    .1666667    .5270463    2.122974    2.877026
---------+--------------------------------------------------------------------
    diff |      10   -2.423469    .1723118    .5448976   -2.813265   -2.033673
------------------------------------------------------------------------------
     mean(diff) = mean(apeh3 - modelh3)                           t = -14.0644
 Ho: mean(diff) = 0                              degrees of freedom =        9

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 1.0000
```

Table 6.18: Paired *t*-test result on equal means

The *t*-statistic (0.00) provides enough evidence that Gompertz and the Logistic models means are not equal. That been said, the paired *t*-test suggested that, at the 95% confidence level, there is a reason to believe that the Logistic model is the most accurate model among the three anlaysed models with the lowest MAPE 6.28%.

6.6 Structural Breaks and Chow Test

Following the recommendation made in Chapter Five to test the validation period of the model for structural changes around Covid-19 pandemic years, a dummy variable (*break*) was added to the model which took the value 1 after 2018. Moreover, an interaction variable (*breakx*) of the regressor, LnInstalledCapacity, and the dummy variable, break, was also added to allow for the test.

Based on the results from the three models, observed cost data between 1996 and 2022 was plotted along with predicted values from the three estimated models against the installed capacity levels over the same period of time. Results came out as follows:

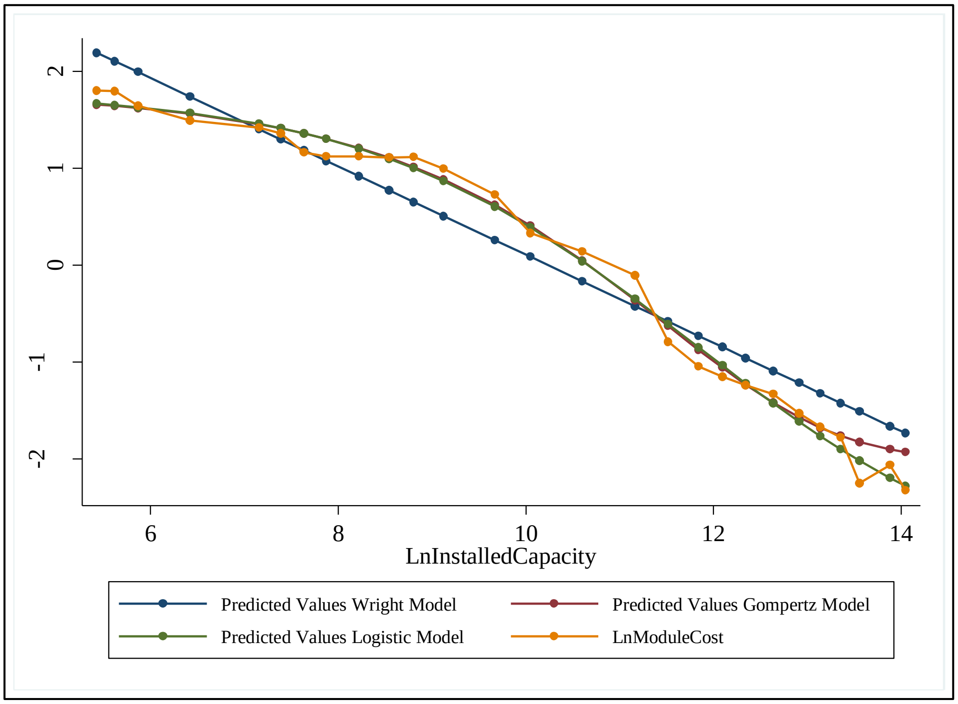

Figure 6.20: Observed price data and predicted prices against cumulative capacity levels (1996-2022)

Figure 6.20 shows that Wright's model provided results that are far from observed prices in the original data set; predictions that are less accurate compared Gompertz and the Logistic models according to the chart. Therefore, Wright's model represents the model where the risk of having structural breaks resides.

Consequently, the structural break test in this analysis focused on Wright's model but could be run to test other models if there is a need (based on the linear regression structural breaks test results). Should Wright's model support the null hypothesis of no structural breaks, it would be more relevant to make the same conclusion on both Gompertz and the Logistic models.

With that said, regression model was performed with the two new coefficients to measure the stability of the original model's coefficients, and test for potential of change in the slope from 2019 as follows:

```
      Source |       SS           df       MS      Number of obs   =        27
-------------+----------------------------------   F(3, 23)        =    177.84
       Model |  50.4345916         3  16.8115305   Prob > F        =    0.0000
    Residual |   2.1742274        23  .094531626   R-squared       =    0.9587
-------------+----------------------------------   Adj R-squared   =    0.9533
       Total |   52.608819        26  2.02341612   Root MSE        =    .30746

------------------------------------------------------------------------------------
       LnModuleCost |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------------+---------------------------------------------------------------
LnInstalledCapacity |    -.46476   .0262994   -17.67   0.000    -.5191644   -.4103556
              break |   .7513203   7.859652     0.10   0.925    -15.50761    17.01025
             breakx |  -.0887445   .5734205    -0.15   0.878    -1.274955    1.097466
              _cons |   4.733042   .2552267    18.54   0.000     4.205066    5.261019
------------------------------------------------------------------------------------
```

Table 6.19: Regression with dummy and interaction variables (2019 and beyond)

The resulted *p*-value for both coefficients are insignificant. However, in order to decide on the presence of structural breaks, Chow test is performed which results in *F*-test statistic that helps accept or reject the null hypothesis (H_0) that there is no structural breaks. If the *p*-value is significant, this should provide enough evidence to reject the null hypothesis and confirm that there is a structural break. Tests of coefficients *break* and *breakx* resulted in the following:

```
 ( 1)  break = 0

       F(  1,    23) =    0.01
            Prob > F =    0.9247
```

Table 6.20: F-statistic for the dummy variable on structural break

And for *breakx* it was:

```
( 1)  breakx = 0

      F(  1,    23) =    0.02
           Prob > F =    0.8784
```

Table 6.21: F-statistic for the interaction variable on structural break

Both results didn't provide enough evidence to reject the null hypothesis of Chow test. Therefore, The null hypothesis was accepted that there is no structural breaks in the model after 2018.

To confirm the result, and since the policy change in China happened in the second half of 2018, it is worth adding a dummy variable and check whether 2018 was affected by any potential structural break following changes in the market. The same procedure was done but dummy variable "*break*" started in 2018 this time instead of 2019. The following regression result was obtained as seen in Table 6.20:

Source	SS	df	MS
Model	50.5316892	3	16.8438964
Residual	2.07712984	23	.090309993
Total	52.608819	26	2.02341612

Number of obs	=	27
F(3, 23)	=	186.51
Prob > F	=	0.0000
R-squared	=	0.9605
Adj R-squared	=	0.9554
Root MSE	=	.30052

LnModuleCost	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LnInstalledCapacity	-.4552378	.0272082	-16.73	0.000	-.5115222	-.3989534
break	2.188177	5.5256	0.40	0.696	-9.242398	13.61875
breakx	-.196732	.4067246	-0.48	0.633	-1.038106	.6446419
_cons	4.658695	.2589959	17.99	0.000	4.122921	5.194469

Table 6.22 Regression with dummy and interaction variables (2018 and beyond)

The observed *p*-value for both coefficients are still insignificant for 2018 and beyond. Chow test is performed again to obtain *F*-test statistic result that helps deciding on the presence of structural breaks. If the *p*-value is significant, this should provide enough evidence to reject the null hypothesis and confirm that there is a structural break. Tests of coefficients *break* and *breakx* are seen on Table 6.23 and Table 6.24 respectively:

```
( 1)  break = 0

      F(  1,    23) =    0.16
           Prob > F =    0.6957
```

Table 6.23: F-statistic for the dummy variable on structural break

```
( 1)  breakx = 0

      F(  1,    23) =    0.23
           Prob > F =    0.6332
```

Table 6.24: F-statistic for the interaction variable on structural break

One more time, both results didn't provide enough evidence to reject the null hypothesis of Chow test. Therefore, the null hypothesis was accepted that there are no structural breaks in the model from 2018 and beyond. However, caution must be taken around major disruptive events such as policy changes in China, or the global Covid-19 pandemic where several factors affected the market unexpectedly.

6.7 Cost Forecasts until 2030

Using the Bloomberg New Energy Finance (BNEF) 10-year forecast dataset on cumulative installed capacity and production forecasts, scenarios were made on solar PV modules cost between 2023 and 2030 using the estimated models. BNEF forecasts predict 19% increase in installed capacity for 2023 from 2022. However, forecasts towards 2030 decrease on yearly basis compared to previous year. For example, the increase from 2029 to 2030 is 12% only which indicates possible saturation levels in the market. Results are plotted against time as seen in Figure 6.21. A detailed discussion on these results will be carried out in Chapter Seven:

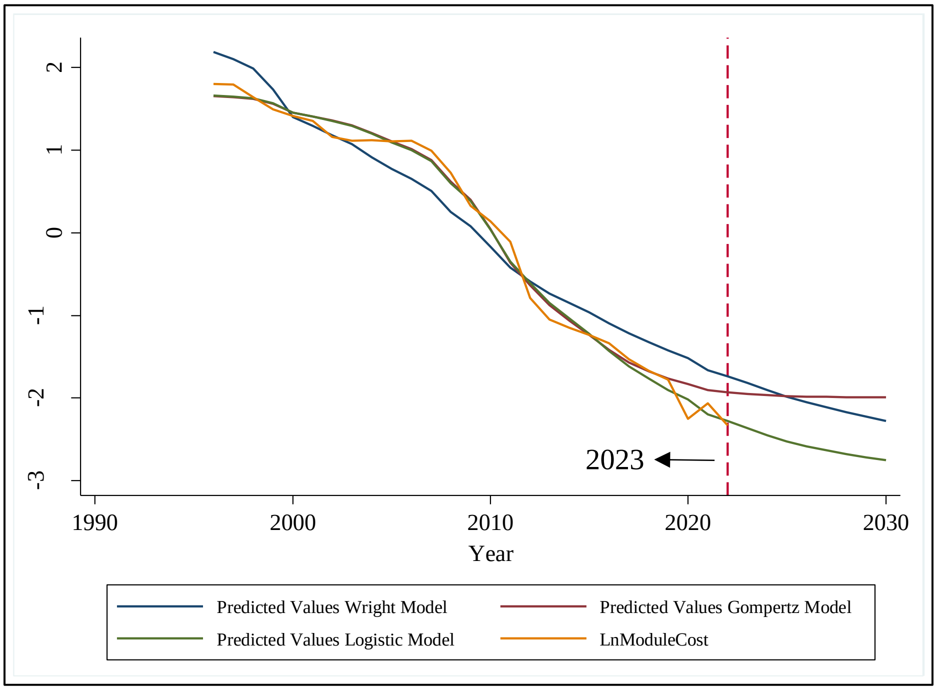

Figure 6.21: Models Forecasts until 2030 versus time

Forecast and predicted values were plotted again against the installed capacity (the independent variable used to estimate the models) as shown in Figure 6.22 and Figure 6.23 (with the reference line to the forecast period):

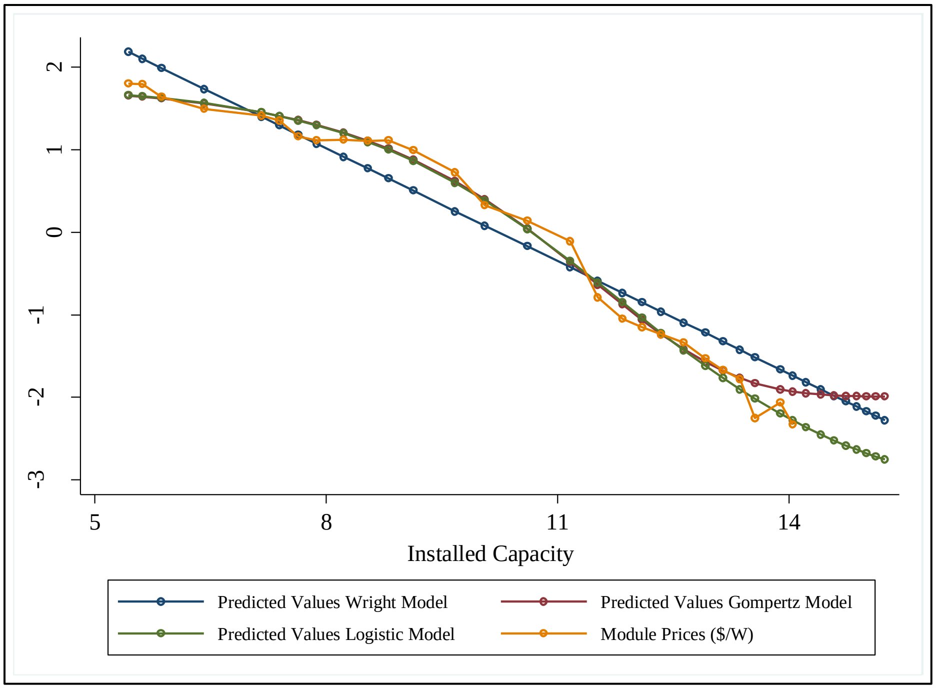

Figure 6.22: Models Cost Forecasts Values ($/W) versus Installed Capacity (MW)

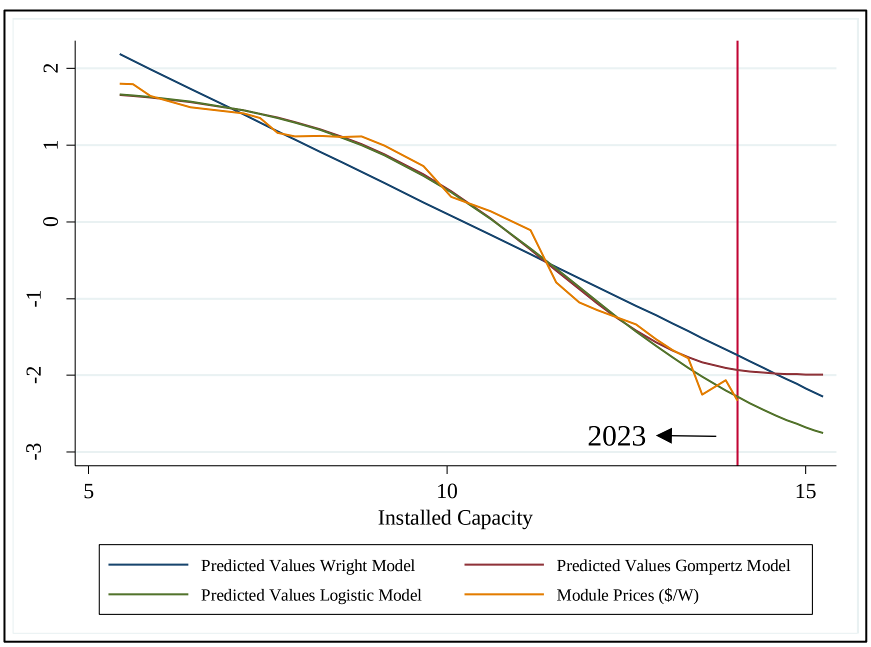

Figure 6.23: Models Forecasts Values versus Installed Capacity (MW) – Reference line

Figure 6.22 and Figure 6.23 show how Wright's model is forecasting a constant decrease in solar PV module prices, yet it is higher than current levels in the market and will remain higher until it matches the real observed prices according to the estimated model. Moreover, Gomeprtz model is close to Wright's observations at the beginning of the forecast period but flattens out quickly and the price decrease stops. On the other hand, the Logistic model is the only model that has a forecast of ongoing decreasing prices from current levels, but flattens out slower than Gompertz at the end tail of the curve.

6.8 Summary

This chapter explained how the data was collected, refined and used in this research. Data splitting helped to run regression models on the training subsets and keep some of the observations out for validation. All regression models came out with significant results on coefficients estimation. High R^2 values in models might hold the risk of the presence of over-fitting in the models. The fitted lines for Gompertz and the Logistic look more reliable than Wright's line, which under- and overestimated cost at many points.

Gompertz model estimated faster initial growth rate which could be explained by the speed of the double exponential slope coefficient. Models' assumptions on the residuals were met with few outliers in Gomeprtz and the Logistic models when residuals were plotted against time.

Using the APE values from the three models on the validation dataset, the Logistic model gave the lowest SSE, MAE, MSE and RMSE values among the three models. It was followed by Gompertz which behaved better than Wright. MAPE value was the lowest in the Logistic model as well. Again, Gompertz gave lower MAPE than Wright using the validation APE values.

Looking at the training dataset, all forecast error measurements were significantly lower, which justifies the data splitting and highlights the risk of biased unreliable models if the estimation is judged based on the training dataset.

The hypotheses testing helped answering the three research questions. The MAPE values are significantly different between the three models. This result allowed the researcher to test the second hypothesis where the Logistic model's MAPE was significantly lower than Wright's. Gompertz model was equally good as Wright at this point. The third hypothesis was run to determine which model is the best performing model between the contemporary models, Gompertz and the Logistic. The Logistic model is significantly different from Gompertz which means it is the best performing model based on this analysis.

When the forecast was made until 2030, the flattening effect was clear in the contemporary models. However, Gompertz appeared to have flattened much faster than other models given the double-exponential nature of the model.

6.9 Conclusion

The purpose of this chapter was to highlight the results of the statistical analysis, using the methods described in Chapter Five, to determine if the nonlinear experience curve equation could reduce error compared to Wright's conventional experience curve model, and if the reduction in error is statistically different between the proposed models. Tables and graphs are included in this chapter to display and confirm the results. Regression models' evaluation metrics were used to evaluate the models performance through the goodness-of-fit values and the residuals. The results were also reported for the standard error of the regression models which includes MAPE value. The results varied between models as the functional form changed. Non-linear experience curve equations reduced the error significantly at 95% confidence level (α=0.05). However, Wright's model showed significant values and behaved well with training, validating and test datasets.

Next chapter will discuss in detail these findings, the practical significance of this research, contribution to knowledge, recommendations for the renewable energy cost analysis methods, limitations of the research and potential future research topics to further enhance our understanding of the effects of experience and learning in the manufacturing process.

Chapter Seven: Conclusions and Recommendations

7.1 Chapter Overview

The purpose of this thesis was to determine if contemporary experience curve models, that mathematically allow for a “flattening effect” later in the production process, could be implemented to reduce the error in the cost estimates for solar PV modules. To do this, three models were investigated in this comparative study. Wright’s conventional power-law model was used as the reference model. Nonlinear Gomprtz and the Logistic models were the contemporary curves in the comparison. These two models were then statistically compared to Wright’s experience curve using solar PV production data.

Experience curves have been widely used as a strategic cost forecasting and planning tool. Conventional experience curve theory assumes a constant learning rate regardless of the number of the units produced (Hogan, 2020). However, theoretical and empirical evidence indicates that the learning process ceases, and manufacturing enters a production steady state (Jaber, 2019).

Consequently, contemporary experience curve models attempted to incorporate plateauing (forgetting) components into experience curves (Badiru, 2012). Building on earlier literature on renewable energy technologies (Nemet, 2006; Rubin et al., 2007; Schilling & Esmundo, 2009; Hansen et al., 2017; Rypdal, 2018), an area of increasing interest was the study how far contemporary models can influence the overall performance of the solar PV technologies cost forecasting models.

This chapter contains the context for the results provided in the previous chapter, as well as the conclusions of the research. This is followed by a discussion on the potential implications of the results at the technological cost analysis in general. The chapter will conclude with the limitations of the study, as well as conclusions and recommendations drawn from this research.

7.2 Conclusions of the Research

Based on the results stated in Chapter Six, the major contribution to the literature is that there is evidence for a more accurate alternative model, predicting the effects technological learning within solar energy industry, than Wright's conventional experience curve.

Both Gompertz and the Logistic improved upon Wright's model estimates with a reduction of approximately 14.6% and 17.4% in MAPE values respectively. The same applies to other error measurements where contemporary models successfully reduced the forecast error compared to Wright's model. The lowest SSE, MSE and RMSE values were seen in the Logistic model, followed by Gompertz model.

The hypotheses testing provided evidence that the mean is different between the three samples, and at least one of the contemporary models are statistically better than Wright's model. This model was the Logistic model, while Gompertz didn't show statistical difference from Wright despite the lower MAPE value. On the third hypothesis, there was enough evidence to say that the Logistic model is different from Gompertz, being the best performing model among the three models.

By now, these conclusions answered the first, the second and the third questions that this research aimed to investigate. Figure 7.1 shows how Wright's model was less accurate at the beginning of the forecast period compared to Gompertz and the Logistic model. In fact, contemporary models were found to be more accurate– as models – than Wright's model throughout the entire process, especially when compared to the Logistic curve performance:

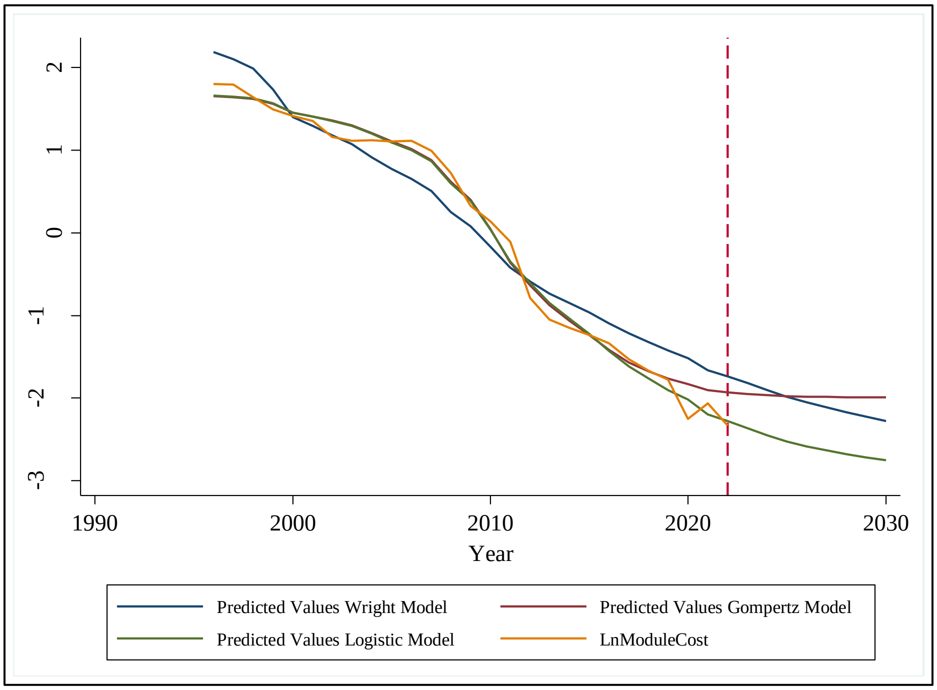

Figure 7.1: Estimated models performance against cumulative capacity (Logarithmic)

From Figure 7.1, Gompertz and the Logistic model performed very well in the training period with some fluctuation caused in early 2000s due to Silicon shortage. The validation period was tested for structural breaks from 2019 onwards to measure the effect of Covid-19 pandemic pressure on supply chains and global shipping prices. There was no statistical evidence of structural breaks, hence, caution is recommended when dealing with forecast models during major disruptive events such as the pandemic period. Wright's model, however, was closest to the actual observations in the middle when the fall in cost was "linear", while performing less accurately at the beginning and at the end of the forecast period. In cost terms, this difference in estimates could result in big savings (or losses) in investments and, indeed, better resource allocation.

7.3 Implications and Significance of the research

In cost forecasting literature, there is a well-established fact that no single forecasting model is the "best" for all situations under all circumstances. In reality the "best" is the robust and accurate for a long-time horizon and, accordingly, users of the model have confidence to use it repeatedly (C.-W. Chu & Zhang, 2003).

Results from the analysis show that there is reason to believe that models that allow the flattening effect can potentially provide more accurate cost forecasts. They also show that Wright's experience curve may not be the best method for estimating costs. By extrapolating from actuals, the method for Wright's model may not incorporate enough of the variability of technological learning. The results emphasise that Wright model is valid and accurate, however, with time passes, the amount of error increases. The conclusions from that study are there is potential for a more accurate cost estimating model using non-linear models. Gompertz and the Logistic curves show promise as a way to improve emerging technologies cost estimating.

This study was unique in three primary areas. (1) It statistically investigates non-constant learning rates in renewable energy cost estimates, through models that allow for the flattening effect, using solar PV modules costs – one of the most promising renewable energy technologies. (2) It introduces Gompertz and the Logistic models as potential experience curve models in energy technologies experience curves field. (3) it emphasises the need for a theoretical framework to analyse technological change that includes Economic-Social-Political (ESP) elements. All technological changes are affected by these three factors. This research dealt with one the economic (E) factors, cost. However, more research is needed to formulate a solid framework that reflects true changes in the market.

Using the future forecast until 2030, analysts and decision makers could also use these forecasts to understand different scenarios on possible future outcomes. Today, there is no way to determine which scenario will be true in 2030. However, managers can establish strategies today around these three possibilities to prepare better for the future.

For example, forecast from Gompertz model can be used to draw the conservative cost estimate scenarios. This is because the cost curve “stops” faster in the double exponential Gompertz curve. On the contrary, the Logistic model and Wright’s models could serve more ambitious forecasts. Based on this, managers and policy makers can consider different potential outcomes in their future plans.

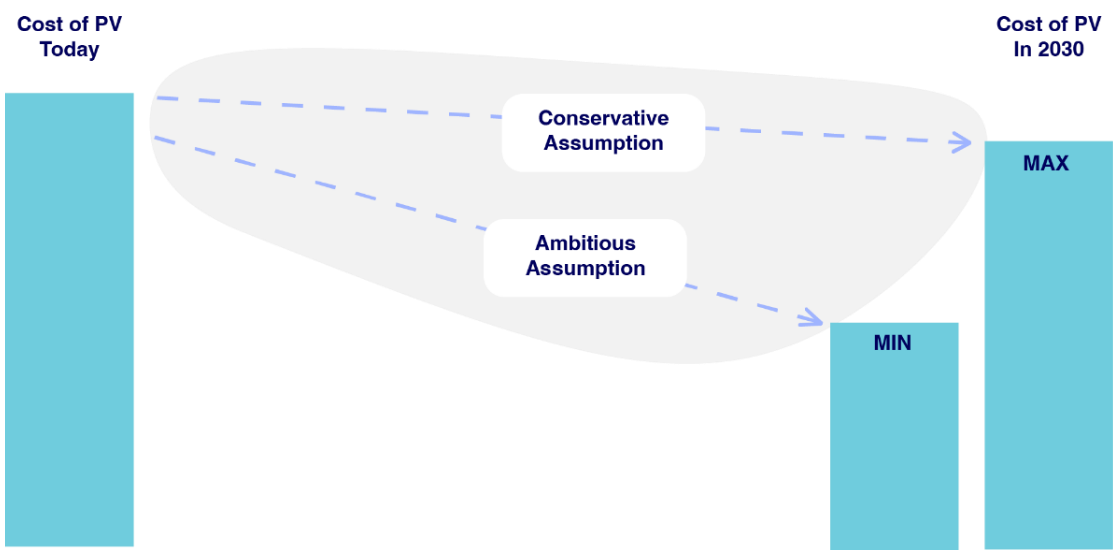

Figure 7.2: Potential future scenarios based on estimated models

Gompertz curve and the logistic possess similar properties which make them useful for the empirical representation of the experience curve phenomenon. It does not appear in literature that either curve has any substantial advantage over the other in the range of phenomena which it will fit. However, it has been found in practice that the symmetric logistic gives better fits on cost data showing an inflection about midway between the asymptotes, which is slightly different from Gompertz asymmetric model.

Analysing renewable energies from nonlinear curves perspective could reveal some surprising and important implications for both government and industry. Therefore, non-linear models might be used as a framework for planning technological change. They introduce the trend and the boundaries for actual experience curve cost curve. Non-linear experience curves can serve as tools for designing entry and exit strategy for public policy formation and/or managerial interventions on certain technologies. Not only they provide a target for the entry or intervention, but also to design exit strategy from a certain market or for the direct subsidies. The end of each non-linear curve provides an opportunity for managers and policy makers to decide on the next step that determines the future of a certain technology (IEA, 2000).

For example, in solar PV market, more radical innovations might be needed to break the technological lock-in in this industry, or it could be a redesign decision for current modules as current product is not improving anymore (technological learning has stopped). Following a profitability analysis, sometimes management decides to retire certain products once they reach the end of the tail.

Nevertheless, there was no clear evidence of any “first mover” benefits using these curves given the slow initial starting phase. However, Christensen (1992) saw this as an advantage that non-linear curves have where in some cases it helps avoid the disadvantage of entering the market too early.

This research agrees with Henderson’s conclusion long time ago when he said: “The experience curve is a valuable conceptual framework for long-range strategy development. It is not suitable for cost control or forecasting over short time spans. For effective application, it requires careful analysis of the definitions of cost components and the definitions of products and markets. It can be misleading when applied to policy decisions if it is used without reference to the effects that will be common to competitors” (Henderson, 1984).

7.4 Limitations of the Research

Understanding the limitations of the research conducted is important to draw reliable conclusions and recommendations. One limitation is related to the dynamics of analysing emerging technologies, which is part of the whole knowledge generation process. Studying emerging technologies implies dealing with limited data and theories, which might be challenging for the forecasting process. This could prevent analysts form using certain useful techniques due to the shortage in data (e.g.: nonlinear models) and leave the research vulnerable to data uncertainties. At the end, this is how knowledge is built as part of the whole knowledge generation process. Therefore, for research purposes, access to cost data must be made easier - especially for emerging technologies.

Another limitation is the accuracy of the reported data as actual prices. However, the fact that many studies from different countries have used these datasets and come with reliable results should help reduce this risk.

The results presented here emphasise the caution against the estimation of experience curves in general on the basis of a single right-hand side variable as a surrogate for experience. After analysing literature on experience curves, this cost/performance model may mask underlying statistical insignificance. The methods used were backed up by the best practice methods used in studies on experience curves. The accuracy of the estimated learning rates remains a major issue. Cross-technology studies can help to increase confidence in estimated learning rates using contemporary models. This observation, however, makes it hard to generalise the result of this research to any other emerging technologies. It would be hard to draw conclusions outside the solar PV modules field without further research and analysis.

Although non-linear experience curves in technology forecasting seem to provide useful insights at an aggregate industry level (e.g.: solar PV industry) about the potential for future improvements, the application of this framework at the managerial level, to plan component technology development, seems to be unclear yet (Christensen, 1992).

7.5 Recommendations for Future Research

Future research is needed to provide a proof on technological learning. The relative stability of the learning curve over a large spectrum of technologies and over time supports the hypothesis of technology learning as a fundamental property of the learning system. However, proof will require a solid theoretical platform but would increase the predictive value of learning curves and provide reliable extrapolation procedures.

There is also a need for more research into the nature of the real processes that experience curves tend to capture. To unlock the full potential of experience curves, they should be part of a proper learning system in the organisation for each technology. This learning system includes key data and information that help understand the dynamics of the resulted learning rates and cost predictions.

Moreover, the promising results of both Gomeprtz and the Logistic models opens the door to further research that help understand other aspects of these curves and test them using different methodologies. They should be tested on various emerging technologies to determine whether they can be used in different fields. There are other curves that account for the flattening effect (e.g.: DeJong, Boone’s, etc.) that could be investigated to see whether they provide similar significant results.

7.6 Summary

Carrying out a quantitative technology experience curve analysis includes gathering historic data related to production and cost changes in a technology of interest and comparing the rate of technology change over time against recognised characteristic patterns of technology performance changes. Once a classic pattern is identified, a reliable projection of technology change can be made, and appropriate action taken to plan for or meet specific technology function or performance objectives.

This thesis has reviewed a large volume of literature on the experience curve theory, its applications, and limitations, and has challenged the constant learning rate in technological cost forecasting models represented in the experience curves.. The review has provided a systematic overview of the different functional forms of the experience curve models, their advantages and limitations in analysing the technological change process, and how to address those limitations when estimating technological learning rates. It also emphasised that energy-economic models now also include experience curve relationships to endogenously include technology dynamics. Finally, the developments of solar PV energy technologies were reviewed focusing on solar PV modules, and the applications of the experience curve approach in predicting their technological developments were examined. The first part of the conclusion summarises the key insights gained from the review of the experience curve approach, and then, the suggestions for future analyses foreseeing emerging technologies are outlined.

This research sought to contribute to a deeper understanding of the problem of climate change and, specifically, of the effects of technological innovation on climate change mitigation efforts, and environmental patents on economic growth.

Happy Forecasting!

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Appendix 1: Data Sources

1. Bloomberg New Energy Finance (BNEF) and Bloomberg L.P (Bloomberg Terminal)
2. Our World in Data: https://ourworldindata.org/

   Our World in Data is a database that was produced as a collaborative effort between researchers at the University of Oxford and a non-profit organisation called Global Change Data Lab. Data from their databases is fed by contributions from scientists and researchers from all over the world. Their databases are trusted in research and media (e.g: Royal Statistical Society, BBC, Science, The Guardian), and they are used in teaching at leading universities such as University of Cambridge, University of Oxford, MIT, and Harvard University. All these are resources available to solar PV technologies cost (price) analysts as they store historical data on renewable energy technologies and other technologies from different industries (Nagy et al., 2013; Lafond et al., 2018).
3. International Energy Agency (IEA): https://www.iea.org/data-and-statistics

   By way of background, the International Energy Agency (IEA) is an intergovernmental organisation that was established in 1974 in the wake of the 1973 oil crisis. Since then, the IEA has been working with governments and industry on various energy projects providing analysis, data, and policy recommendations. Data collection has always been at the heart of the IEA's work with official energy statistics from more than 100 countries, according to the IEA (IEA, 2012).
4. Statista website: https://www.statista.com/