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Improving the analytical framework for quantifying technological progress in energy technologies

Srinivasan Santhakumar [a,*], Hans Meerman [a], André Faaij [a,b]

[a] Energy and Sustainability Research Institute Groningen, University of Groningen, the Netherlands
[b] Netherlands organization for Applied Scientific Research - TNO Energy Transition, Utrecht, the Netherlands

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ABSTRACT

This article reviews experience curve applications in energy technology studies to illustrate best practices in analyzing technological learning. Findings are then applied to evaluate future performance projections of three emerging offshore energy technologies, namely, offshore wind, wave & tidal, and biofuel production from seaweed. Key insights from the review are: First, the experience curve approach provides a strong analytical construct to describe and project technology cost developments. However, disaggregating the influences of individual learning mechanisms on observed cost developments demands extensive data requirements, e.g., R&D expenditures, component level cost information, which are often not publicly available/readily accessible. Second, in an experience curve analysis, the LR estimate of the technology is highly sensitive towards the changes in model specifications and data assumptions.. Future studies should evaluate the impact of these variations and inform the uncertainties associated with using the observed learning rates. Third, the review of the literature relevant to offshore energy technology developments revealed that experience curve studies have commonly applied single-factor experience curve model to derive technology cost projections. This has led to an overview of the role of distinct learning mechanisms (e.g., learning-by-doing, scale effects), and factors (site-specific parameters) influencing their developments. To overcome these limitations, we propose a coherent framework based on the findings of this review. The framework disaggregates the technological development process into multiple stages and maps the expected data availability, characteristics, and methodological options to quantify the learning effects. The evaluation of the framework using three offshore energy technologies signals that the data limitations that restrict the process of disaggregating the learning process and identifying cost drivers can be overcome by utilizing detailed bottom-up engineering cost modeling and technology diffusion curves; with experience curve models.

1. Introduction

IEA's world energy outlook indicates that the global primary energy demand is set to grow by more than 25% to 2040 under current and planned policies, requiring more than 2 trillion USD a year of investment in new energy supply [1]. Development and deployment of emerging low-carbon energy technologies are needed to meet the growing demand and displace the existing operational energy assets, i.e., decarbonization. Currently, the emerging low-carbon energy technologies are less economically competitive than conventional energy technologies, which hinders their deployments in the market. However, in the long-term, with continued support in terms of R&D and deployments, these technologies pose significant potential for cost reduction and value to the future energy system (in achieving the emission targets and lowering system costs) [2]. To stimulate their developments in the market, in terms of informed policy actions and investment decisions, a clear understanding of the process of technological change and insights on the sources of technology cost reduction is essential.

Several hypotheses, including endogenous growth theory, innovation systems theory, and experience curve approach, have been applied in the literature to describe and analyze the technological change [3],; refer to Appendix A. However, the experience curve approach remained as a widely adopted methodology to anticipate technology cost developments [4,5]; prominent examples include solar PV modules and onshore wind technology [6]. The experience curve provides an analytical construct to quantify the influence of the individual learning mechanisms behind the technology cost developments, which are

* Corresponding author. Energy and Sustainability Research Institute Groningen, Energy Academy, Nijenborgh 6, 9747 AG, Groningen, the Netherlands.
E-mail address: s.santhakumar@rug.nl (S. Santhakumar).

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Abbreviations

C	Celsius
CCGT	Combined Cycle Gas Turbine
DM	dry matter
ESM	Energy System Model
EU	European Union
EUR	EURO
GW	Gigawatt
HVDC	High-voltage direct current
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
JRC	Joint Research Centre
kW	Kilowatt
kWh	Kilowatt-hour
LBD	Learning-by-doing
LBS	Learning-by-searching
LCOE	Levelized Cost of Energy
LR	Learning Rate
m	meter
MW	Megawatt
O&M	Operation and Maintenance
OECD	Organization for Economic Co-operation and Development
OTEC	Ocean thermal energy conversion
PR	Progress Ratio
PV	Photovoltaic
R&D	Research and Development
SET-plan	Strategic Energy Technology Plan
TRL	Technology Readiness Level
UK	United Kingdom
USD	United States Dollar

crucial in designing effective policies [7]. Also, experience curves are used in endogenizing technological change in energy system models and scenario developments, through which the long-term development pathways and energy system costs are assessed [8,9]. Methodological assumptions and the LR estimates used in these applications are highly influential towards its outcomes [9–12], making it crucial to identify the best practice in projecting the future cost trends of energy technologies. This task forms the main objective of this article. To achieve this objective, a review of state-of-the-art knowledge of the experience curve approach, its use cases in energy technology studies, and uncertainties are made (in Section 2 - 4). Then, as a case study, this article reviews the developments of three emerging offshore energy technologies and examines the application of the experience curve approach in projecting their developments (in Section 5). The technologies are offshore wind, wave & tidal, and biofuel production from seaweed. Finally, the conclusions and suggestions for future research are summarized.

2. Experience curve approach and methodology

2.1. Basic concept

The experience curve approach assumes that the unit cost of technology will decline as it gains experience through production and use. This phenomenon was first reported in 1963 by Wright [13], who found that the cost reduction in unit labor costs of airframe manufacturing was a constant percentage for every doubling of its cumulative capacity. Arrow explained that the cost reduction achieved was a product of the experience gained in the process [14], and the relation between them was commonly referred to as the learning curve. Later, the Boston Consultancy Group [15] extended the learning curve concept to the total cost of technology, and also to an entire industry by including production cost, R&D, and other cost elements necessary to deliver the product to an end-user. This extended relation became known as the experience curve. In literature, the term *"Experience Curve"* and *"Learning Curve"* has been used interchangeably to represent the technology cost reduction as a function of its cumulative output. Nevertheless, in this article, the term *"Experience Curve"* is used to represent the extended relation between the cumulative output (experience) of the technology and its overall performance (generally measured in technology unit cost).

When plotted on a log-log scale, the relation between the cumulative output of the technology and its unit cost takes a linear form, as shown in Fig. 1. In mathematical form, the relation is expressed as a power function,

$$C_t = C_0 * X_t^{-E} \tag{1}$$

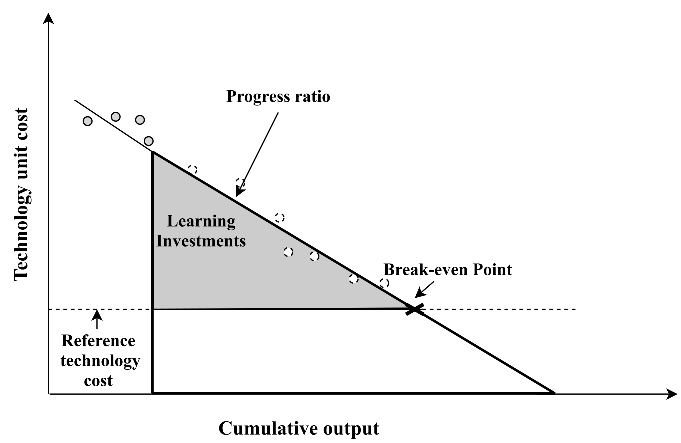

Fig. 1. Representation of an experience curve.

where C_t is the specific cost of the technology in the year t

C_0 is the specific cost of the technology at one unit of cumulative production or sales.

X_t is the cumulative production or sales of the technology in the year t, and E is the experience parameter.

Taking logarithm on both sides of the Eqn. (1) gives a linear model,

$$Log(C_t) = Log(C_0) + (-E)*Log(X_t) \tag{2}$$

The parameter E in the Eqn. (2) indicates the steepness of the experience curve (Fig. 1) and is used to calculate the Progress Ratio (PR) and Learning Rate (LR) of the technology,[1] as shown below,

$$PR = 2^{-E} \tag{3}$$

$$LR = 1 - PR \tag{4}$$

Eqn. (1) is commonly referred to as a single-factor experience curve (SFEC) model and the corresponding LR as a learning-by-doing rate (LBD) in the literature. However, one should remember that the cumulative output is only used here as an aggregated proxy for experience gain, and the resulting LR approximates the overall progress of the technology [16]. The limitations of the SFEC model and disaggregating

[1] For example, Progress Ratio (PR) of 70% results in 30% of Learning Rate (LR), which says, the technology achieves 30% cost decline for each doubling of its cumulative production.

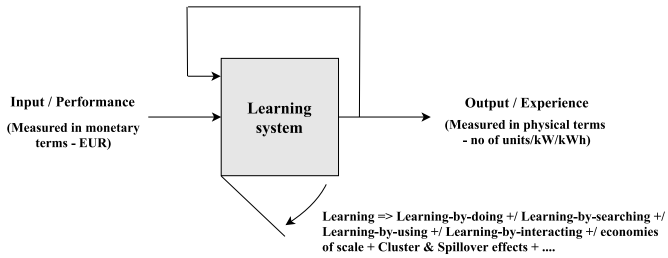

Fig. 2. Model of a learning system, adapted from a previous study [20].

the learning process are discussed further in the following section.

2.2. Multi-factor models and the process of experience curve analysis

Fig. 2 shows a simple model of a technology learning system, which depicts the continuous process of transforming inputs to outputs with a feedback loop that facilitates learning. Several learning mechanisms and factors generally exist inside a learning system, influencing technological progress [17–20], see Fig. 2. However, those factors are not explicitly quantified in the SFEC model, which has been raised as a critical concern [18,21,22]. Multi-factor and component-based experience curve models were developed to overcome those concerns [16,23–25]. Table 1 compares different forms of the experience curve models, application examples, limitations, and data requirements.

The process of experience curve analysis generally involves three steps [26],

- data collection & verification
- data processing and experience curve parameter estimation
- analysis of results

The first step, data collection & verification, is considered the most time-consuming and challenging part of the analysis. The data requirements in the experience curve analysis increases when the learning process is disaggregated, and the influence of individual learning effects is to be quantified, see Table 1. In the second step, the collected data is processed (e.g., correction for inflation effects, exchange rates) and brought into the same scale for homogeneity, e.g., cost information in the same currency. The processed data is then used to derive the experience curve and calculate the experience curve parameters, including LR, learning investment, and breakeven point. In the third step, the experience curve parameters are analyzed to identify the sources of technology cost reduction, interpret the technology's progress in the market, and quantify the uncertainties of the cost projections.

Furthermore, in an experience curve analysis, the performance and experience metric does not necessarily have to be technology unit cost and cumulative output, as shown in Fig. 2. The metrics depend on the learning system boundary [18]. One could fix the boundary at an industry level to measure the overall progress of the technology in the market, or at a firm level to analyze developments in the production process. In either case, a performance and experience metric representing the learning system boundary must be chosen for consistent results. For example, to analyze the developments in the wind turbine production process (at the firm level), utilize the turbine production cost as a performance metric and cumulative units of turbine produced as an experience metric. Although, in the end, to make an investment decision, LCOE is the most convenient and essential metric for project developers. LCOE provides a holistic picture of the development of an energy generation technology in the market by accounting unit cost of the technology, operational expenses, cost of capital, technology lifetime, and all other elements essential for generating energy. For this learning system boundary (overall progress of technology in the market), utilize LCOE as a performance metric and cumulative energy production (in kWh) as an experience metric.

Table 1
Comparison of different experience curve models and their data requirements.

	Single-factor experience curve (SFEC)	Two-factor experience curve (TFEC)	Component-based experience curve (CFEC)
Method	• SFEC uses cumulative output as an aggregated proxy for learning and quantifies the development in a single parameter, Eqn. (1).	• TFEC includes another learning mechanism in the experience curve formulation, besides cumulative output, as shown in Eqn. (5) [a]. $C_t = C_0 * X_t^{-E} * K_t^{-R}$ (5) • TFEC can be extended as a *multi-factor experience curve model (MFEC)* by including other learning mechanisms in the equation.	• In CFEC, the total technology cost is expressed as the sum of its component costs [16], as shown in Eqn. (6). $C_t = \sum_{i=1}^{n} C_{0,n} X_{n,t}^{-E_n}$ (6) The subscript *n* in the equation refers to the index of individual technology components. • Finds application in analyzing the development of emerging technologies, where data availability is limited.
Limitations	• Aggregated in nature • Potential omitted variable bias, i.e., when the experience curve model leaves out one or more relevant independent variables from its equation, the estimated learning effects are found to be biased (commonly in the upward direction).	• Requires periodic accounts of data, including public & private R&D expenditure, which are not often publicly available/readily accessible. • Presence of multicollinearity can bias the LR outcomes, i.e., there should be a trade-off between omitted variable bias and multi-collinearity to maintain the accuracy of the LR outcomes [30]	• The overall experience gain of each technology component is represented by its cumulative output alone . Thereby, the limitations of the SFEC applies to the outcomes of individual technology components.
Application Examples	• Solar PV [6,25,31] • Onshore wind [6,26,32]	• Onshore Wind [32–34] • Solar photovoltaics [25,30,35]	• Power plants with carbon capture technology [23] • Carbon storage technology [36] • Wave & tidal technology [29] • Parabolic trough (Solar power) [37]
Data Requirements	*Performance metric:* Technology unit cost (specific investment cost in €/MW or cost of energy generation in €/MWh) *Experience metric:* Cumulative output of the technology (e.g., cumulative capacity installed in MW or cumulative energy generated in MWh)	*Performance metric:* Technology unit cost *Experience metrics:* Cumulative output + public and private R&D expenditure + scale parameter + market-pull mechanisms + Feedstock prices (e.g.., cumulative installed capacity or energy generated + Knowledge stock in € + turbine rated power in MW + Feed-in-tariff cost in €/MWh + steel price in €/ton)	*Performance metric:* Technology unit cost *Experience metrics:* Cumulative output of component 1 + Cumulative output of component 2 + …. + Cumulative output of component n

[a] If R&D expenditure is included in the Eqn. (5), K_t refers to cumulative R&D expense, and the corresponding LR *($1-2^{-R}$)* is referred to as the Learning-by-Searching (LBS) rate.

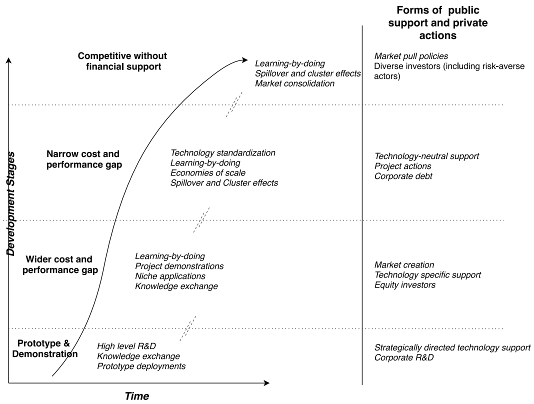

Fig. 3. A non-linear model of energy technology development process, adapted from [10].

The choice of the experience curve model in analysis depends on the access to the available data (Table 1) and the development status of the technology itself. For technologies that are under development or have matured, either SFEC or MFEC are applied to quantify the progress in an aggregated manner or separate the influence of individual learning effects on overall cost developments [18,27]. However, for emerging technologies (with limited commercial deployments), studies generally follow the CFEC or SFEC model to derive future cost trends (by assuming learning experiences from analogous technologies) [28,29]. The applicability of different forms of experience curve models is further examined in *Section 5*.

3. Applications

In this section, the three most common use cases of the experience curve approach in energy technology studies are discussed.

3.1. Technology analysis

The experience curve approach has been primarily utilized to anticipate technology cost developments, more commonly using the SFEC model due to its most straightforward construction and minimal data requirements [4,18]. However, the aggregated nature of the model poses limitations in explaining the underlying learning process.

Here, the qualitative context of the technological change process is briefly discussed to emphasize the role of distinct learning mechanisms on technology's progress. Technological change, in general, is a complex process that involves several stages and diverse characteristics [19], as shown in Fig. 3. The process begins with a technological innovation[2] entering the prototype and demonstration stage. The primary purpose of this stage is to exhibit the performance and viability of the technology in the market. At this stage, high-risk R&D activities and knowledge exchange with existing technologies are also conducted to improve the reliability of the technology. Once the technology achieves a series of successful demonstrations in the market, small-scale commercial deployments are initiated. These early-stage implementations enable learning opportunities for the technology in the market, initiate supply chain developments & market creation, and build a track record for the technology [38,39].

Then, after a prolonged period of experimentation with many commercial smaller-scale units in the market, the upscaling of the technology begins. The upscaling can refer to unit- or industry-scaling, or both depending on the nature of the technology.[3] Both unit- and industry-scaling of the technology occur concurrently in practice [40], yielding rapid technology cost reductions. However, at a certain level, the unit-upscaling potential of the technology saturates. After that, the increased deployments in the market continue to bring incremental improvements for the technology, i.e., towards achieving cost-competitiveness. Finally, the development process of the technology ends with saturated development potential or commonly replaced by new technology in the market [19].

Besides the learning mechanisms and processes mentioned above, spillover effects (knowledge exchange with other technology sectors/next-generation designs) and cluster effects (mutual benefits for interrelated technology in the energy system) also slowly emerges in the market over the entire development process [19], adding benefits to the broader network of energy systems and society.

In summary, the technological change process is complex, and the role of distinct learning mechanisms influencing the progress of technology transforms as technology pass through each development stage towards market maturity. An aggregated application of the experience curve approach (SFEC model) would oversee these transformations and individual influences of learning effects. Therefore, future studies should utilize the qualitative context of technological change to disaggregate the learning process and hypothesize the factors influencing the developments (also quantify their influences). Such practice will improve the approach's capacity in explaining the sequential stages of technological change and its characteristics with empirical evidence.

3.2. Policy factors and technological learning

Policy measures are crucial in stimulating the development of emerging technologies in the market. However, improperly designed measures could stagnate the development process and limit cost reduction opportunities for the technology. Such actions also increase the risk of sub-optimal technologies being locked-in in the system, leading to higher societal costs [19].

Policy measures can be categorized into two types: technology-push and market-pull [24]. Measures that incentivize breakthrough innovation such as improved technology design, new materials, or new production processes are commonly referred to as technology push measures. Measures that incentivize market expansion and creates opportunities for incremental improvements through production and use are referred to as market pull measures.[4] Both types of policy measures are crucial for technology development, but the role can differ widely depending on the development stage of the technology. Conventionally, in the early development stage, technology-push measures like R&D spending are considered to play a significant role in bringing innovation to the market and closing the cost-performance gap of the technology. When the gap becomes narrow, market-pull instruments are used to accelerate technology adoption in society. In a generic notion, the need for support at the unit level of the technology (e.g., € amount for each

[2] Most technological innovations are considered to be a product of existing technologies combined in innovative ways, referred to as *combinatorial evolution* [39].

[3] Energy supply technologies can be classified into two groups, one which exhibits unit upscaling potential, and one that does not (i.e., modular technologies). Coal power plant, wind turbine, nuclear power plant technology, are examples of technologies that exhibits stronger unit-scale economies. Solar photovoltaic module technology, on the other hand, have limited potential for unit upscaling and are commonly referred as modular technologies..

[4] Examples of technology-push measure include, R&D funding, prototype building and technology demonstrations. Examples of market-pull measures include Feed-in-Tariff mechanisms, tax credits for technology investments.

MWh) and the level of risk perceived by investors in the market declines as technology passes through each development stage towards maturity. However, the cumulative support required will increase when market-pull mechanisms are necessary for realizing increased deployments in the energy systems.

The cumulative learning investment estimate and breakeven point serve as the primary indicators for policy-related discussions (Fig. 1). *Learning investments* refers to the additional costs, as investments, necessary in making the technology cost-competitive in the market. Breakeven point refers to the cumulative capacity (not the time) at which the technology under study will become cost-competitive in the market. Decision-makers should see this learning investment in terms of both risk and benefit to society. A very high estimate of learning investment is an indication of a wider cost-performance gap. Hence, supplementary R&D programs or other technology-push measures should be deployed to cut initial higher costs, i.e., bringing step-change in the experience curve (refer to section 4.3) [20]. Focusing on market-pull measures at such an early stage might not be a cost-effective solution. Because market pull measures are generally deployed to increase the production and use of technology in society, which incentivizes incremental improvements and can lead to higher societal costs to achieve cost-competitiveness in the market.

Furthermore, the contribution to the learning investment of technology comes from both public and private organizations. High-risk activities such as early-stage R&D projects and prototype deployments are often subsidized through public funds. Private firms, on the other hand, contribute to the learning investments majorly when the technology has achieved a certain level of market readiness, i.e., limiting their exposure to risks. Also, these investments are made by private firms to gain early-mover advantage in the market [20]. The effectiveness of public policy measures in developing the technology is assessed by calculating the ratio of cumulative learning investments to the sum of public funds spent [26], as shown in Eqn. (7). This ratio provides insights on the role of public and private learning investments in the technology development process, e.g., a value of more than 1 indicates that public policy measures were effective in stimulating private investments in the market.

$$Cost\ efficiency = \frac{Total\ learning\ investment}{Total\ Government\ subsidy} \tag{7}$$

In summary, cumulative learning investment and cost-efficiency are two policy-related parameters commonly used in experience curve studies, which provide much functionality in assessing policy measures rather than designing them. This limitation arises from aggregated applications of the experience curve approach (SFEC model), where the sources of technology cost reductions are not quantified separately (a key element in designing effective policy measures). Increased application of multi-factor experience curve models would fill this gap and improve the experience curve approach's ability to design effective policy measures in the future.

3.3. Endogenizing technological change in energy system models

Energy transition models are commonly used to analyze the future energy system mix, climate change adaptation & mitigation strategies on the national and international levels. They are also used to study interactions between energy, economy, and the environment. Two approaches are generally used to model interactions between them: the top-down approach and bottom-up approach. Both approaches mainly differ in how comprehensive technologies are modeled (bottom-up) and how general economic concepts are described consistently (top-down). A third hybrid approach also exists, which combines the merits of the bottom-up and top-down approaches.

The energy system model outcomes (ESM) are greatly influenced by the underlying technology inputs and their development assumptions. Commonly, the technology development assumptions are exogenous (i.e., developments are modeled as a function of time or annual efficiency improvements) in the energy system models, where investments for emerging technologies are postponed to the future until they become cost-competitive. This outcome contradicts the basic understanding behind the energy technology innovation process, where early investments are necessary to stimulate learning opportunities and achieve cost reductions for emerging technologies. To overcome this limitation, technological change is endogenized in ESM's, commonly using the experience curve construct [9]. The experience curve brings computational difficulties in ESM due to its non-convex nature. However, they are solved by applying piecewise linear approximations to the experience curve and integrating them into the Mixed Integer Programming (MIP) framework. To further understand the modeling approaches and how technological change is endogenized, refer to past studies [8,9,41–43]. Some ESM's that have endogenized technological change includes, MESSAGE [44], MARKAL [45], POLES [46], NEMS [47,48], ERIS [49], ESO-XEL [9] in bottom-up approach and DEMETER [50], FEEM-RICE [51] and MIND [52] in top-down approach. Here, some of the research implications found on endogenizing technical change in ESM's are summarized.

- Endogenizing technological change in the energy system model moves the optimal investment for emerging low-carbon technologies to earlier planning years. It was thereby acknowledging the need for early investments and the development potential of low-carbon technologies in the market.
- Endogenizing technical change on the energy system model is found to have a considerable influence on the aggregate cost of climate policy actions (lower cost of CO_2 mitigation policies) comparing to ESM models with exogenous learning assumptions, implying the benefits of earlier actions on low-carbon technologies.
- The absolute values of the ESM outcomes, like the cost of CO_2 mitigation, future technology mix, technology deployment levels, and cost trajectory, vary substantially across studies, depending on the LR's used (refer to sub-section 4.4).
- ESM, like MARKAL, takes technological spillovers and clustering effects into account. These learning dynamics represent system-level benefits where similar technologies in the market gain experience from each other, representing the actual case of the technological change process [19]. Such models have also found lower costs to comply with a given climate policy target than the models that do not account for spillover and cluster effects.
- Top-down models generally provide insights related to the innovation and diffusion process of technologies in the market, capturing strategic considerations, and their influence on macroeconomic factors. On the other hand, Bottom-up models provide insights into the future technology mix, technology cost developments, and knowledge stock. Studies should treat these insights as complementary, which is essential in analyzing the energy transition pathways and designing effective policy recommendations.

4. Uncertainties in experience curve approach

As discussed in the previous sections, the experience curve approach provides a strong analytical construct to describe and anticipate technology cost developments. The approach has also achieved overwhelming empirical evidence across many sectors, including, manufacturing [53], medical procedures [54], aerospace and defense industry [55,56], ship production [57,58], semiconductors [59,60], consumer products [61,62]; in addition to energy sector [4,5,18]. However, several limitations and uncertainties are found to distort the outcomes of the experience curve analysis. This section briefly discusses those concerns and provides recommendations to overcome them.

4.1. Limitations of the experience curve approach

The experience curve approach poses three limitations in analyzing the technological change process. First, experience curves are empirically observed relations and not a law that states the unit cost of the technology declines with an increased cumulative output [26,63], i.e., the correlation between the two variables does not imply causation. Bottom-up cost models can be used here to identify the cost drivers. In bottom-up cost models, the technology system is decomposed into several sub-systems. Those sub-systems' technical and economical design parameters can be varied (based on observed developments/expert opinions) to quantify their influence on overall cost developments, e.g., application of bottom-up cost model and experience curves to identify the factors influencing cost reduction in PV technology [64].

Second, the approach's abilities are limited in foreseeing incremental improvements of the technology, not radical ones [26]. The substitution of key materials, introducing an improvised production process, or shifts in the market could lead to a drastic change in the technology cost. These deviations depend on several external factors, including institutional changes (e.g., research focus), target market developments (e.g., market growth or innovative technology applications), the progress of other technologies/sectors in the market (e.g., cluster effects), which are not directly analyzed in the experience curve approach. Hence, the innovation, a process that is fraught with uncertainties, could not be foreseen by extrapolating a linear trend line. Here, innovation systems theory can offer insights to explain the sequential process of technological change and hypothesize the prospects of technology in the market (incl. radical changes). The innovation process is studied by mapping the activities (how different stakeholders interact within the technology innovation system and existing technology systems at different geographical scales) in the technology innovation system, resulting in a technological change [39,65]. When these activities are mapped over time, the dynamics of an innovation system can be analyzed [66].

Third, the approach faces difficulties in isolating individual learning effects (LBD, LBS, scale effects) from observed technology cost developments. From Fig. 3, it is evident that a combination of learning mechanisms generally influences technological progress. Also, the combinations change, and the learning mechanisms co-exist to a greater extent across the entire development process [20,67]. The multi-factor experience curve model attempts to untangle these combinations and quantify their influences separately, but they also require extensive technology data. Simply excluding a learning mechanism (an explanatory variable) from the experience curve model equation, due to data unavailability, introduces bias in the LR outcomes.[5] Here, one solution is to use technology diffusion curves (logistic growth curves) fitted using the unit & industry-scale data. These curves detail the growth dynamics of technology in the market [40,68]. By identifying the uptake of technology unit-scaling and its saturation levels, experience curve studies can interpret the extent of influence of scale effects on technology cost reduction.

4.2. Influence of cost overruns and technology floor cost

Large-scale power plant technologies and industrial process systems have commonly observed cost overruns in their early commercialization phase [23,69], due to delays in construction time, shortfalls in the performance of new system designs, and unforeseen operational issues. Cost overruns are also highly uncertain and short-term, as no reliable methods are available to quantify the magnitude of the effects during the early stage of the development process [70]. Nevertheless, the technological risks resulting in cost overruns are better managed as the technology gain experience through development and deployment in the market.

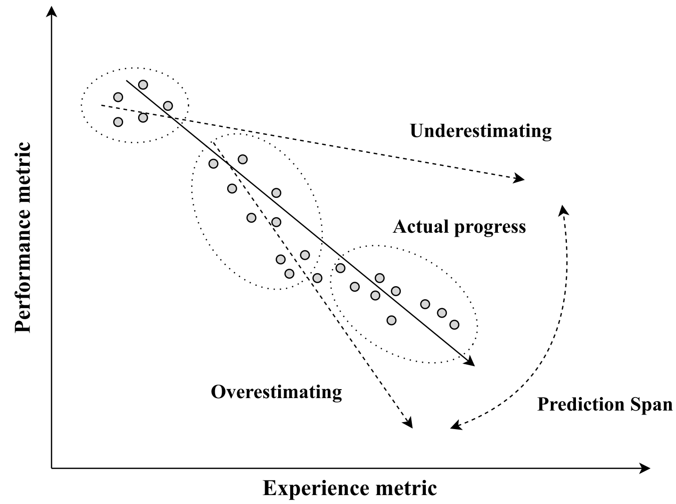

Fig. 4. Influence of short-term effects on LR estimates, adapted from a previous study [71].

The influence of cost overruns observed in the early phases of technology development translates into an upward trend in the experience curves. For an established technology in the market with excellent data availability (technology cost and cumulative output information), the experience curve diminishes this short-term influence and provides stable LR estimates. However, this is different for emerging technologies, where the cost overrun effects are often overrepresented in the LR estimates, as shown in Fig. 4. Besides, the technological risks resulting in cost overruns are part of the learning process and cannot be excluded from the analysis. Therefore, it is important to analyze those technology risks separately to understand their level of impact on LR estimates. For instance, the installation rates [72], system efficiency [73], or construction insurance costs [72] serve as a good proxy for technological risks. Estimating how these factors influence the total technology cost (e.g., using a bottom-up cost model) will result in the approximate estimates of potential cost overruns, through which their impacts on the LR estimates can be understood.

Furthermore, the cost reduction cannot be achieved for a technology endlessly. 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* and is used as a reference cost in experience curve studies (see Fig. 1), e.g., estimation of floor costs for PV modules [63]. The floor costs are also commonly imposed in the energy transition models to prevent the technology costs falling below a specified value [27]. In practice, the cost of mature incumbent technology in the market is used as a reference floor cost, which determines the available learning potential for the technology in the market (not the real potential).

4.3. Influence of market price dynamics and technology structural change

In an ideal case, the experience curve relation should be derived using cumulative output and technology cost. However, private firms generally do not report technology cost information to protect their technological advantage (production process techniques, development strategies) over competitors. Hence, the market price data is very often used to derive LR estimates, making it essential to understand whether the approach's cost decline assumption holds for price-based experience curves.

[5] If an independent variable whose true regression coefficient is nonzero and is excluded from the model, the estimated values of all the regression coefficients will be biased; unless the excluded variable is uncorrelated with every included variable [33].

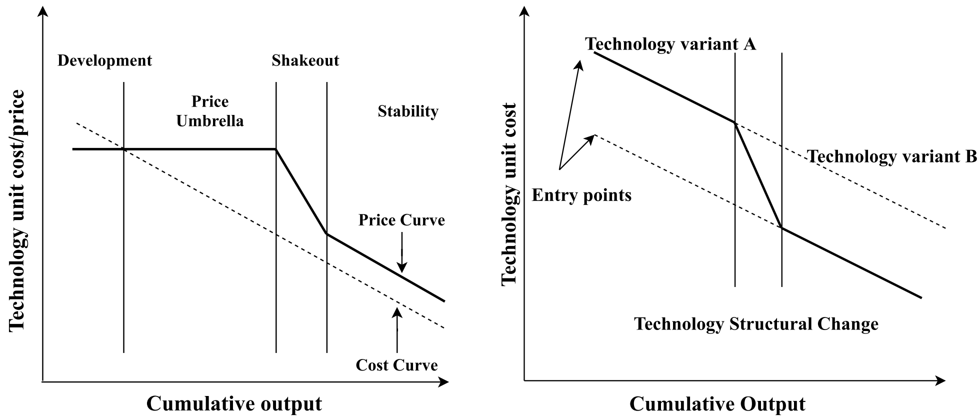

Fig. 5. 1) Price-cost relation for new product development 2) Effect of technology structural change in the experience curve. Referred from [20].

The technology cost represents the sum of all cost elements necessary to build and deliver a final product to an end-user. The market price, on the other hand, includes a profit margin in addition to the total cost. The profit margins set by the firms are dynamic and depend on various internal (-firm) and external (-market) factors, including sales strategies, market power, response to policies & regulations. These influences introduce anomalies in the price-based experience curve, referred to as market-structural change [20], e.g., CCGT [73]. Boston Consulting Group reported a price-cost relation for a new product introduction in the market [20], see Fig. 5.1. This relation provides a guideline to understand the firms' pricing strategies at different stages of market development, and the same can be used to interpret the impact of profit margins on LR estimates. In the long run, i.e., in the market stability phase, all producers are inclined to use an optimal combination of the total cost and profit margin to stay in the market. Therefore, the price- and cost-experience curve will have the same slope (i.e., LR) in the market stability phase, which is more likely to represent the actual development rate of the technology. To identify whether the technology is in the market stability phase or not, market share developments over the years can be analyzed (entry and exit of competitors).

Furthermore, research & development activities are continuously conducted to develop a technology variant or introduce an improved production process. This is to bring the technology cost down, improve performance, and start a new business cycle (see Fig. 5.1). This event is referred to as technology structural change, which translates into a step-change in the experience curve and a possible increase in LR (see Fig. 5.2). IEA's report on experience curves indicates two examples where the changes in the production process of PV modules during 1976–1996 and technology switch from collector to absorber technology of solar heating systems in 1982 introduced a structural change in their experience curves [20]. In a price-based experience curve, the technology-structural change could go unnoticed, as the profit margins set by the firms for the technology variant generally mask the cost developments. Therefore, one should not misconstrue technology-structural change for market ones and vice versa, in a price-based experience curve.

4.4. *Learning rate – a constant, variable or a range*

In literature, past studies have reported a wide range of LR's for energy technologies [18,27], e.g., 113 LR observations of onshore wind technology ranging from −3 to 33% were reported under different data periods & geographical scope [32]. The observed variations are high enough to bring significantly different outcomes in its applications [20, 74], like optimal technology choice in an energy transition model or priority in learning investment decisions. To better understand the nature of the LR parameter and avoid misinterpretation, the root causes of such differences are discussed in this section.

Grübler [19] argues that technology cost reduction happens quite fast in the early stage of the development process, and the potential for cost reduction declines drastically as the technology matures. The experience curve (cost curve) can intuitively explain this slow-down phenomenon in its log-log linear relation [20]. Hence, the overall LR of technology does not necessarily have to change in theory. However, in a price-based experience curve, the market- & technology-structural change, and cost overruns, are found to alter the LR 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 LR estimates significantly.

Influence of data periods: Technological change process (from innovation to market maturity, in Fig. 3) takes considerable time, generally decades [75]. The longer the technology is under development and deployment in the market, the more records of data depicting its progress are available. Thereby, stable LR estimates can be achieved. However, this is different for emerging technologies, whose market price data is often influenced by the overrepresentation of external factors (e.g., market power [73]) and short-term development characteristics (e.g., cost overruns, unit upscaling). These influences generally result in over-/underestimation of the learning effects of emerging technologies, as shown in Fig. 4. As a rule of thumb, a period of 10–12 years' worth of historical data or 2–3 orders of magnitude of the cumulative output is suggested to achieve stable LR estimates in the experience curve studies [76,77]. Even so, noticeable differences in the LR estimates are observed. Nemet [78] analyzed how changes in data periods influence the solar PV module technology's LR estimates. A dataset covering global PV module prices and cumulative installed capacity between 1976 and 2006 was used in the study. He reported that by changing the data periods (keeping a minimum of 10-years' worth of data at all cases), the LR estimates of PV technology had varied from 14% to 25% (from 5th to 95th percentile in the LR distribution, total observations = 253).

Influence of the model specification: The prevalent form of experience curve approach, SFEC model, utilizes the cumulative output of the technology as a proxy for overall experience gains and results in an aggregated LR estimate (referred to as LBD rate). When the experience curve model is extended (i.e., other learning mechanisms like R&D, scale effects are included in the equation), the LBD rate is altered (generally reduced [22,24,79]), and the influence of individual learning effects are quantified separately. This change implies that the LR estimates are sensitive towards the inclusion of the factors in the experience curve model equation and indicates likely positive bias in the SFEC model's outcomes (i.e., omitted variable bias).

Here, as an example, the variations observed in the LR estimates of onshore wind technology (from past literature) across different experience curve model specifications and data periods are shown to emphasize the impacts mentioned above, see Table 2. First, in Table 2, eight different model specifications formulated by Söderholm et al. [33]

Table 2
Impact of data assumptions and model specification on LR estimates of onshore wind. Model specifications are referred from Ref. [33]. Then, a comparison is made between the outcomes (LR estimates) of [33] (in column 6) and other studies that have utilized similar experience curve model specifications (in column 7).

No	Model Specification	Performance metric	Experience metric	Remark	*Summary of the findings from the study* [33] *Data: 1986–2000, Scope:* DK, DE, UK, and ES	Comparison with LR estimates reported in past literature (under same experience curve model specifications)
1	SFEC	Investment cost (€/MW)	Cumulative installed capacity (MW)	–	LR: 5% This estimate is commonly referred to as LBD rate but depicts the overall progress of the technology	[80] reported ~4% LR for global average turbine price (1990–2012). [6] reported ~7% LR for onshore wind investment costs (1983–2014).
2	SFEC	Investment cost (€/MW)	Cumulative installed capacity (MW)	Observations before the year 1992 were removed	LR increased from 5% to 8% with the shorter dataset (i.e., overestimation). The increase in LR is potentially caused by excluding early cost overruns and market dynamics effects from the underlying data.	[18] reviews SFEC model LR from the past literature. LR estimates range from (−)3 – 32% under different data periods and geographical scope (no of observations = 73).
3	SFEC	Investment cost (€/MW)	Cumulative energy generated (MWh)		LR: 6% Here, it is reminded again that cumulative energy generation (MWh) is not an appropriate experience metric to analyze the chosen learning system boundary (onshore wind investment cost)	Cumulative energy generation (MWh) is not considered an appropriate experience metric to analyze investment cost developments.
4	TFEC	Investment cost (€/MW)	Cumulative installed capacity (MW), Scale parameter	Wind generation level was used as a proxy for scale effects (due to lack of data on turbine size)	LBD rate is reduced to 1.8% (statistically significant only at 15% level), and the inclusion of scale effects in the equations shows increasing returns to scale in developments of onshore wind technology.	[34,81] reported that the scale parameter is not statistically significant in MFEC, implying constant returns-to-scale.
5	TFEC	Investment cost (€/MW)	Cumulative installed capacity (MW), Cumulative R&D expenditure (€)	No assumption on knowledge depreciation and time lag	LBD rate is reduced to ~3%. Learning-by-searching rate: ~8%.	LBD: 13.1% LBS: 26.8% (1980–1998, Scope: Global) [24]
6	MFEC	Investment cost (€/MW)	Cumulative installed capacity (MW), Knowledge stock (in €)	Time lag: 2 years Knowledge depreciation: 3%	LBD rate is reduced to ~4%. Learning-by-searching rate: 16%.	LBD: 9.73% LBS: 10% (1979–1997, Scope: Global, Knowledge depreciation: 3%) [49]
7	MFEC	Investment cost (€/MW)	Cumulative installed capacity (MW), Knowledge stock (in €), Scale parameter		The scale parameter is not statistically significant in the model LBD: 2%, LBS: 12%	[34,81] reported that the scale parameter is not statistically significant in the MFEC model, implying constant returns-to-scale.
8	MFEC	Investment cost (€/MW)	Cumulative installed capacity (MW), Knowledge stock (in €), Scale parameter, Feed-in-price (€/MWh)	Feed-in price is included here to analyze policy effects	The scale parameter is still not statistically significant in the model. However, the Feed-in-price parameter is positively correlated to the developments. LBD: 3%, LBS: 13%	[82] reported that the feed-in price parameter is a determinant for the diffusion process, but not for invention and innovation (significant).

Table 3
Summary of pitfalls and recommendations for experience curve analysis.

Pitfalls	Recommendations
Choice of experience metric	The experience and performance metric in the experience curve model should represent the scope of the learning system under study.
Minimum data requirements	Minimum of 10–12 years (or at least 2–3 cumulative doublings), with no missing years in between, worth of historical data is suggested.
Technology cost information is not available	Analyze the market share developments (entry and exit of technology suppliers) to interpret the possibility of monopolistic/oligopolistic market behaviors.
Excluding the potential impact of cost overruns on data points	Analyze the technological risks resulting in cost overruns separately to understand their potential impacts on the LR estimates.
LR –constant or a variable?	Perform a sensitivity analysis, for instance, by removing some observations from the available dataset or independent variables in the experience curve model; to examine and understand the causes of LR variations.
Difficulties in reproducing the LR estimates	Explicitly document the learning system boundaries, model specification, and criteria for data collection, facilitating the reproducibility of the results and understanding the causes of variations better.

(which accounts for different learning effects and data assumptions), and their corresponding LR results are summarized (Scope: DK, DE, UK, and ES, Data period: 1986–2000). Also, to compare, LR estimates reported in other studies under similar experience curve model assumptions are summarized. It has to be noted that the geographical scope of the learning system (onshore wind investment cost) varies across the studies and their impacts are beyond the scope of this comparison, refer to Ref. [32]. Key observations from Table 2.

- *Impact of data period variations in LR estimates:* It is vital to recognize whether the experience model omits the influences of specific learning mechanisms or factors by excluding observations from the dataset (model 2). If those factors are inherent to the development process, the LR estimates would be biased.
- *Impact of experience curve model specification in LR estimates:* Introducing the scale effects (model 4,7,8), R&D expenditure (model 5), knowledge stock (model 6,7,8), and feed-in-price (model 8), in the experience curve model equation, lowers the LBD rate. Thereby, confirms positive bias in model 1 outcome.

In summary, the learning rate estimates of the technology are highly sensitive to the changes in data assumptions and the inclusion of independent variables (learning mechanisms) in the experience curve model equation. Future studies should conduct sensitivity analysis, for instance, by removing observations from the dataset or changing independent variables from the experience curve equation; to examine and understand the differences in the LR outcomes. Sensitivity analysis will serve two essential purposes.

- The LR range will give a good sense of uncertainty about the outcomes of the experience curve analysis.
- The sensitivity analysis will improve our understanding of the causes of the LR variations. It is crucial that studies clearly explain whether the resulting LR estimate represents the overall performance of the technology or individual learning effects or biased by external factors like market dynamics, to avoid any misinterpretation in their applications.

4.5. Summary of recommendations

It is challenging to provide guidelines on data collection and LR estimation that will yield better projections of technology costs. Based on the review in previous sections, some recommendations are summarized in Table 3 to avoid common pitfalls in the process.

5. Examining the application of the experience curve approach

This section examines the application of the experience curve approach in projecting the developments of three emerging offshore energy technologies (offshore wind, wave & tidal energy technology, and biofuel production from seaweed). These three technologies provide a compelling case as they are at different development stages and pose different technology characteristics. Offshore wind (well-established technology) and wave & tidal (emerging technology) are considered large-scale electricity production technology, but they are profoundly different in their characteristics. Offshore wind parks are realized by constructing a large number of wind turbines placed on fixed or floating structures. The performance of the wind parks is site and climate-specific. Wave & tidal technologies are generally subsea structures. Tidal stream devices utilize the energy of flowing water in tidal currents to generate electricity, and wave power converts the periodic up-and-down movement of ocean waves into electricity. Besides, the sea conditions influence the design of the conversion equipment in wave technology [83]. Biofuel production from the seaweed (emerging technology), on the other hand, involves a value chain of processes from offshore feedstock cultivation, transportation of feedstock to shore, and then biofuel conversion process to deliver a range of fuel products, including biogas, ethanol, and other possible chemicals. The first part, sub-section 5.1–5.3, discusses the characteristics of the offshore technologies and the outcomes of past studies analyzing their developments. Then, in sub-section 5.4, the insights from the review are consolidated, and methodological recommendations for future analyses are proposed.

5.1. Offshore wind technology

The world's first offshore wind farm, Vindeby, was constructed in Denmark in 1991 with a capacity of 4.95 MW. Then, by 2020, 36 GW of offshore wind capacity was installed worldwide, and the industry is considered to have gained significant experience in different fronts [84]. In literature, studies have applied a range of methodologies, including bottom-up cost modeling and experience curve approach, to quantify the developments and foresee the prospects of the technology in the market. Much of the early works commonly assumed learning experiences from analogous technologies (onshore wind and marine engineering practices). Chapman and Gross [85] projected offshore wind investment costs based on high-cost onshore sites and concluded that a

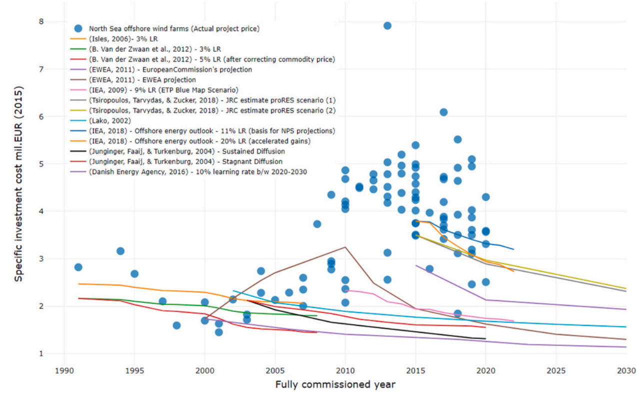

Fig. 6. Comparing the offshore wind project costs (actual) Vs. outcomes of past studies.

15–20% LR was a reasonable expectation for offshore wind investment cost. Lako [86] derived the specific investment cost of offshore wind technology until 2030, utilizing a bottom-up cost modeling approach and LR assumptions from onshore wind. A detailed review of early works can be found in Ref. [87]. Assuming learning experiences from analogous technologies is reasonably acceptable at the nascent stage of the development process. However, in offshore wind, the contribution of component costs to the total technology investment cost [88], risks, and technical factors are different from the onshore kind. Hence, a simple extrapolation of the technology cost in an aggregated manner should be interpreted with caution. The long-term projections (investment cost) of the early works might still be reasonable, but the realized offshore wind projects show a different trend, see Fig. 6. A brief note on the underlying data and calculations related to the projections in the figure is provided in Appendix B.

With the continued deployment of projects in the European waters, more primary data (project cost and cumulative installed capacity) is becoming available. Studies have utilized those primary data to derive empirical LR's specific for offshore wind technology; a summary is provided in Table 4. Jamasb [22] reported 8.3% LR for offshore wind investment costs between 1991 and 2001. Isles [89] reported a 3% LR between 1991 and 2007 and highlighted the increasing trend of specific investment costs, which was also confirmed in recent studies [90,91]. Offshore wind investment cost has increased roughly from 2 mil. €/MW in 2000 to ~5 mil. €/MW in 2013. After that, the investment cost declined (with considerable spread). Factors including commodity price fluctuations (copper and steel), limited competition in the market, and the risks associated with the wind farms in deeper waters, were attributed to the increasing investment cost trend. However, those factors' influence was not quantified explicitly [92], making it challenging to extrapolate future investment costs with confidence.

Besides, experience curve analyses (empirical studies) have commonly limited their scope to the offshore wind investment cost and excluded the Levelized Cost of Energy (LCOE) developments. Estimating offshore wind LCOE requires project-specific information, including the cost of capital, capacity factor, and O&M expenditures (see Fig. 7.2), which developers do not publicly disclose. Nevertheless, LCOE is a critical metric that significantly impacts investment decisions and policy actions, making it crucial to understand their developments. Voormolen et al. [90] analyzed the LCOE developments of offshore wind using a bottom-up cost modeling methodology. Assumptions on the cost of capital and O&M expenditures were referred from the available literature. The study reported that the LCOE of offshore wind technology has increased from 100 €/MWh in 2000 towards 200 €/MWh in 2013. After 2013, the LCOE appears to decline, and the improvements in the offshore wind farm's capacity factor have been noted as a critical contributing factor [93]. The investment cost of offshore wind

Table 4
Summary of learning rates for offshore wind technology (only empirical findings).

Source	Experience curve model type	Experience metric	Performance metric	Learning rate	Geographical scope	Data Period	Remarks
[98]	Two-factor experience curve model	Cumulative capacity (MW), R&D expenditure ($)	Specific investment cost ($/kW)	LBD : 1% LBS : 4.9%	OECD countries	1994–2001	In a single-factor experience curve model with cumulative installed capacity as an independent variable, 8.3% LR was found for offshore wind investment cost
[89]	Single-factor experience curve model	Cumulative capacity (MW)	Specific investment costs (€/kW)	3%	Global (Dataset only represents wind farms in European waters, but approximated for global learning)	1991–2007	When analyzing the periodical developments, 10% LR was observed for the first 300 MW of cumulative installations. After that, LR was estimated at −13%, indicating the investment cost increase.
[99]	Single-factor experience curve model	Cumulative capacity (MW)	Specific investment costs (€/kW)	3%	Sweden, Netherlands, UK, Sweden (only monopile foundations)	1991–2008	The investment cost is corrected for commodity price fluctuations. For the period 1991–2005, LR is 5%. The decrease in LR to 3% is attributed to the shift (demand-supply inertia) in the turbine manufacturing and installation services market.
[91]	Single-factor experience curve model	Cumulative capacity (MW)	Specific investment costs (Mil. $/MW)	Negative learning rate (>100% PR)	Denmark, Sweden, the Netherlands, U.K, Germany, Ireland, Belgium, and Finland	1991–2012	

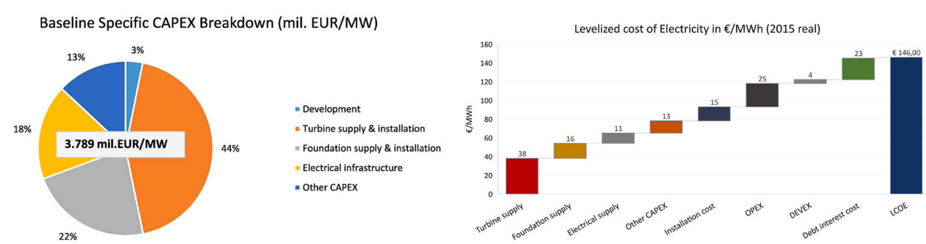

Fig. 7. 1) Specific investment cost breakdown and, 2) LCOE breakdown reflecting average characteristics of offshore wind farms installed between 2012 and 2014 Source [88].

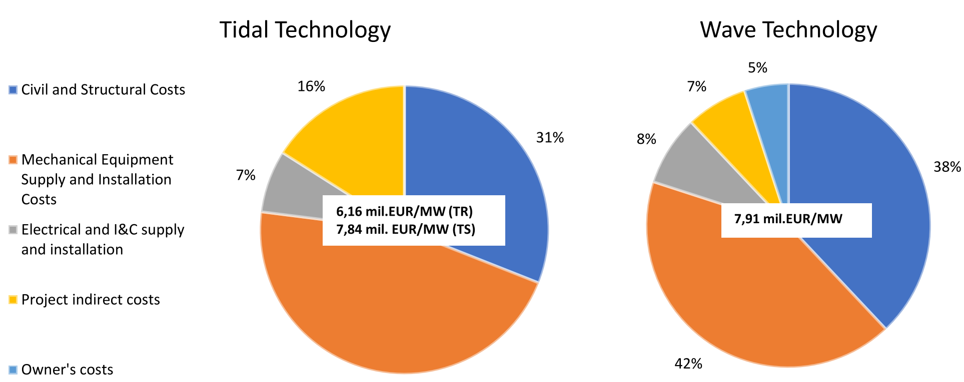

Fig. 8. Generic investment cost breakdown for wave & tidal energy technology [28,104].

technology shows a similar development trend (Fig. 6). IRENA [94] reported more conservative estimates, as the global weighted average LCOE of offshore wind decline from ~131 €/MWh in 2013 to ~106 €/MWh[6] in 2018 (more than 20% decline, LR for LCOE could reach 14% over the period 2010 and 2020 [95]). IRENA also projects that the LCOE of offshore wind technology would fall further, reaching a range of 40–70 €/MWh in 2030 and 25–70 €/MWh in 2050 [94]. It is important to remind here again that the LCOE estimates of offshore wind can vary widely across studies depending on the assumptions of cost of capital, wind farm capacity factor, and O&M expenditures, i.e., careful examination of underlying assumptions is essential to understand the LCOE development trends.

In summary, offshore wind shows a unique development trend where the technology cost (both investment cost and LCOE) steadily increased between 2000 and (around) 2013. After that, a sharp decline in technology cost is observed. Recent auction results in the UK, Netherlands, and Germany also signals promising prospects for the technology. For the first time, Germany's electricity regulator approved auction bids to build offshore wind farms without any subsidies in 2017 [96]. The UK offshore wind market also achieved its cost reduction target four years ahead of its planned schedule [97]. Nevertheless, the process of

[6] 1 USD = 0.82 EUR.

Table 5
Summary of learning rates found in the literature for wave & tidal energy technology.

Technology	LR (%)	Performance Variable	Experience Variable	Source
Tidal stream technology	5–10	Cost of Energy	Cumulative Capacity (MW)	[106]
	12.5–13	Specific Investment Cost	Cumulative Capacity (MW)	[107]
	12	Specific Investment Cost	Cumulative Capacity (MW)	[105]
	12	Specific Investment Cost	Cumulative Capacity (MW)	[104]
	15	Specific Investment Cost & Operation Expenditure	Cumulative Capacity (MW)	[108]
	7–15	Specific Investment Cost	Cumulative Capacity (MW)	[28]
Wave energy technology	10–15	Cost of Energy	Cumulative Capacity (MW)	[106]
	10–15	Specific Investment Cost	Cumulative Capacity (MW)	[109,110]
	13.2	Specific Investment Cost	Cumulative Capacity (MW)	[107]
	9–18	Specific Investment Cost	Cumulative Capacity (MW)	[110]
	12	Specific Investment Cost	Cumulative Capacity (MW)	[105]
	3	Load Factor	Cumulative Capacity (MW)	[105]
	12	Specific Investment Cost	Cumulative Capacity (MW)	[104]
	7–15	Specific Investment Cost	Cumulative Capacity (MW)	[28]
Tidal stream & Wave Energy technology	15–20	Specific Investment Cost	Cumulative Capacity (MW)	[111]
	6–15	Specific Investment Cost	Cumulative Capacity (MW)	[74]

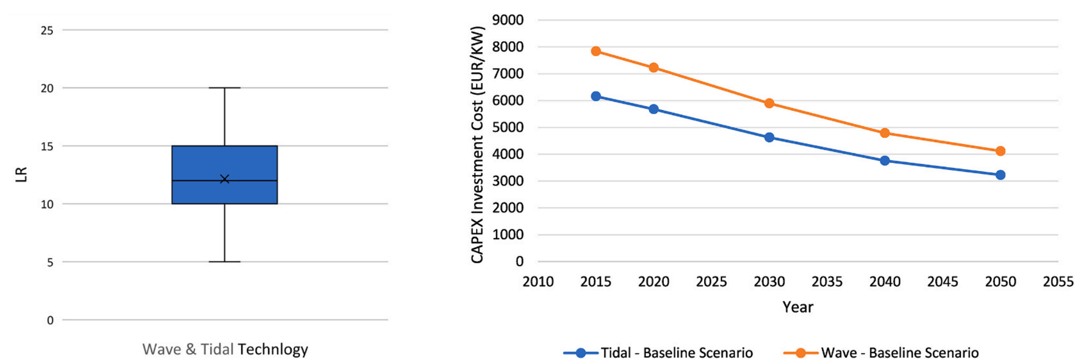

Fig. 9. 1) A summary statistic of LR's found in the literature (from Table 5) 2) Wave & Tidal investment cost projections (12% LR), Source [28].

modeling the factors influencing offshore wind cost developments is still a work in progress. Future studies should focus on utilizing multi-factor experience curve models or similar quantitative methodologies that account for raw material costs, location-specific wind farm properties, scale effects, and soft factors such as cost of capital. Quantifying their influences on the observed cost developments is crucial in unraveling offshore wind technology's technological progress and understanding the prospects of emerging technology variants like floating offshore wind.

Table 6
Component-level LR estimates for wave & tidal energy technology. .

Components (Performance Variable: Cost of Energy (GBP/MWh) Experience Variable: Cumulative Deployment (MW))	Tidal	Wave
	LR (%)	LR (%)
Structure and prime mover	12	9
Power take-off (PTO)	13	7
Station keeping	12	12
Connection	2	1
Installation	15	8
O&M	18	12

Source: [29]

5.2. Wave & tidal energy technology

Ocean energy refers to a group of marine energy technologies, including wave & tidal stream, tidal range, ocean thermal energy conversion (OTEC), and salinity gradient technology. This section focuses on the wave & tidal stream technologies alone and its technological progress, as OTEC and saline gradient technologies are still immature (low TRL).

Wave & tidal technology pose similar characteristics as offshore wind, a compound system where several components make up the technology and hold a significant share in the total cost, as shown in Fig. 8. Since 2010, 26.8 MW of tidal stream and 11.3 MW of wave energy devices have been deployed in European waters. Of this, 11.9 MW of tidal stream and 2.9 MW of wave energy devices are currently on the site, and the rest is decommissioned [100]. As an emerging technology in its prototype & demonstration phase, these early-stage implementations are crucial in exhibiting their market viability. However, to advance to the next step of the development process (initiate commercial deployments), the market sees two milestones as a prerequisite. The first one is the technology design convergence, which increases the investor's confidence, enables mass production of the technology, and aligns supply chain requirements in the market. The tidal sector is showing significant design convergence towards wind-like horizontal axis turbine technology. On the other hand, wave technology still has several different design concepts at the demonstration level, showing a level behind the tidal sector [101]. The lack of technology design convergence also makes the available investment cost estimates highly uncertain for wave technology [29]. Second, a series of demonstration projects with a successful and reliable operational track record is necessary, referred to as "array scale success" [102]. Tidal stream technology has achieved successful operation of demonstration arrays in recent years and is set to enter the early commercialization phase. By the end of 2016, three-quarters of tidal energy companies in the EU started developing full-scale horizontal axis tidal devices, and 14 tidal energy projects were grid-connected and operational. Between the period 2003 to 2018 alone, the tidal stream sector has fed 35 GWh of electricity into the European grid [100]. The wave sector, on the other hand, had slowed down previously due to several technological drawbacks and prominent companies going into administration. Nevertheless, after 2016, the market is recovering and focusing on improving its system's reliability [101,103]. These developments indicate that both technologies are at the nascent stage of the learning process, where technology-specific support, high-risk R&D activities, and prototype demonstrations exist or in need (see Fig. 3).

Past studies have applied the experience curve approach to project the future cost trends of wave & tidal technology. The LR's employed by these studies are generally aggregated, expert opinions, and assumptions referred from past technologies (LBD rate in the SFEC model). A summary of LR's found in literature is shown in Table 5, and its distribution is shown in Fig. 9.1. As emerging technologies in the market, wave & tidal provides limited empirical observations to validate the outcomes of past studies, see Fig. 9.2.

The technology components (sub-systems) of wave & tidal, like electrical infrastructure and offshore installation, are not entirely new to the market. They build on the existing experience gained from conventional electricity transmission technologies and offshore marine engineering practices [19,105]. Besides, site-specific characteristics and scale effects are also expected to influence the future cost trends of wave & tidal technologies [29]. In such a case, applying an aggregated LR (10–15% in the SFEC model) could over-/underestimates their influences in the long-term technology cost projections. Over-promising the development potential at an early stage and not delivering the cost targets might damage the credibility of the wave & tidal sector as a whole, hindering potential learning investments in the market [74]. A disaggregated approach that can account for individual learning effects (or development assumptions at a component-level of the technology) is recommended to avoid those limitations. Carbon Trust [29] utilized a component-based experience curve approach complemented by engineering analyses to derive the cost of energy projections[7] for wave & tidal technology. The learning rates for each cost center were derived using engineering analyses, i.e., by assessing the cost reduction potential in leading wave & tidal devices between the first farm (10 MW) and 200 MW installations, see Table 6. In the study, the cumulative deployment level (MW) and the cost of energy were used as an experience metric and performance metric. Cumulative energy generation (MWh) would have been a more sensible experience metric for extrapolating cost of energy (refer to Table 3). Nevertheless, this is a sound approach to apply for a complex energy system at the prototype & demonstration stage of the development process.

5.3. Biofuel production from seaweed

Biofuels are regarded as an alternative energy source for transport, heating, and industrial sectors in the energy system, i.e., sectors considered as harder-to-abate in energy transition studies. If produced sustainably, biofuels can play a vital role in decarbonizing those sectors. Here, the production of third-gen biofuels[8] from seaweed and its development potential in the North Sea region are discussed.

Seaweeds are forms of algae that grow in the marine environment, which have very little lignin, high growth rates, and a higher carbon dioxide fixation rate. Fundamentally, they do not compete with food crops for arable land and potable water [112]. Based on the pigments, seaweeds are classified into three categories: red, brown, and green, e.g., species-specific to the North Sea region: *Laminaria digitate (Finger kelp; brown seaweed), Saccharina latissimi (Sugar kelp, brown seaweed), Palmaria palmate (Dulse, red seaweed), Ulva lactuca (Sea lettuce; green seaweed)* [113]. Currently, Asia is the largest seaweed producer (China, Korea, Philippines, and Japan alone account for 72% of global annual production), and they are primarily cultivated for food production, fertilizers, and hydrocolloid extraction [114]. The interest in utilizing seaweed as a feedstock for biofuel production, on the other hand, is in its infancy but growing among the industry and academia.

The process of producing biofuels from seaweed involves five steps, as shown in Fig. 10. The first three steps, cultivation, harvest, and transportation, can be highly generalized into one step as *seaweed supply or feedstock supply*. The following two steps, pretreatment and conversion process step, are referred to as the *conversion process*and can vary widely depending on the end-use/products. Current market developments of these two steps are discussed below, *Feedstock Supply:* Seaweed cultivation is not an emerging practice as there are established supply chains for seaweed-based food production [115] and hydrocolloid extraction [116]. However, the case is slightly different if seaweed is to be utilized as a biofuel feedstock. Because productivity, scalability, and a continuous supply of biomass are critical factors in establishing a successful supply chain for biofuel production [112]. Also, most of the existing cultivation methods employed in Asia cannot be directly adopted in the North Sea region, i.e., they are labor-intensive and proven to be not profitable in the western region. Several macroalgal cultivation trials have been conducted in the Atlantic region over the past decade, using different cultivation concepts, including ring, long-lines, and grid system [117]. The production costs reported from those trials vary widely (estimates differed roughly by a factor of 100), and only little consensus was found among them; refer [118] for a detailed review. Recently, Bak et al. [119] reported the results of a new cultivation trial (*Sachharina Latissima*) conducted in the Faroe Islands.[9] A novel concept called Macroalgae Cultivation Rig (MACR) was developed and deployed in the site (at water depth 50–70 m). The study estimated the seaweed production cost based on the empirical data gathered through harvest periods 2015 and 2016. The results of a baseline case are summarized in Table 7. The study also highlighted that by increasing the number of harvests to six harvests per growth line deployment in a year (i.e., increasing the yield), the cost per kg of seaweed was cut down by 75%, to 9.27 €/kg.dw. Nevertheless, it should be noted that constant seawater temperature near the Faroe Islands allow for multiple harvests per year. Future studies extrapolating their cost estimates should understand the differences in climatic and ocean conditions and their impacts.

Due to limited commercial experience and a little consensus found among the outcomes of cultivation trials, the production cost of seaweed on a large-scale is still highly unclear. Within the European project named "*EnAlgae*" [121,122], a detailed bottom-up cost modeling tool was developed to estimate the offshore seaweed production cost. Burg et al. [123] utilized the cost model and quantified the economic prospects of large-scale offshore seaweed cultivation in the North Sea region. The study estimated the production cost of seaweed (*Sachharina Latissima*) about 5.2 €/kg.dw, as a baseline cultivation scenario. The study also reported that seaweed production cost could be reduced up to 1.2 €/kg.dw, through upscaling, reducing the cost of plant material, increasing the yield, and combined use of space (e.g., mussel cultivation, wind farm [118]).

[7] In this study, a baseline breakdown of cost of energy generation was made for wave & tidal energy technology (at 10 MW deployment level). The estimates are 290–330 GBP/MWh for tidal (bottom-mounted) and 380–480 GBP/MWh for wave energy (floating type).

[8] Biofuels are generally characterized by their source, type, and production. First-gen biofuels are made from sugar, starch, vegetable oil, or animal fats using conventional technology. Second-gen biofuels are produced from non-food crops that includes animal fat and dedicated lignocellulosic crops. Third gen biofuels are produced from micro-organisms like algae, which have higher average photosynthetic efficiency of about 6–8% (compared to 1.2–2.2% of terrestrial biomass) [141].

[9] It should be noted that constant seawater temperature near the Faroe Islands allow for multiple harvests per year. Future studies extrapolating their cost estimates should understand the differences in climatic and ocean conditions. (move the footnote, to the end of the paragraph).

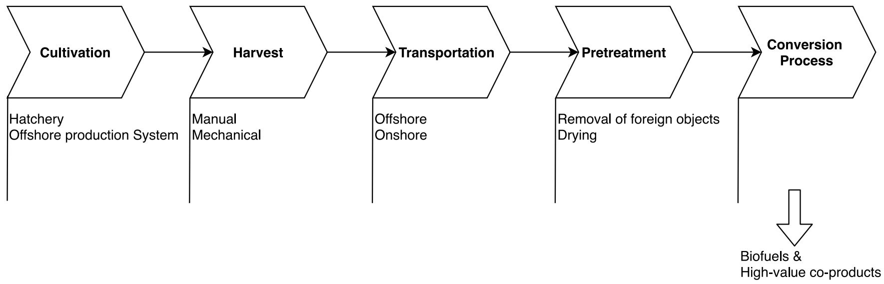

Fig. 10. Conceptual value chain of biofuel production from seaweed, adapted from a previous study [120].

Table 7
Production cost of cultivated seaweed at an offshore site in the Faroe Islands – (findings from real-life cultivation trial). .

Cultivation of Saccharina Latissima in one Macroalgae Cultivation Rig	Cost/Production data	Units
Production data		
Total meters of growth line	2500	m
Number of harvests per year	1	#
Annual yield of harvested biomass	718.75	Kg.dw
Expenditure		
Capital expenditure per year	21,700	€
Operational expenditure per year	4700	€
Total cost per year	26,400	€
Costs		
Cost per kg macroalgae (dw)	36.73	€/kg. dw

Source: [119]

Table 8
Applications of seaweed and their associated market value.

Applications	Value of Seaweed (€ per ton DM) (1 metric ton = 1000 kg)
Hydrocolloids	333–1250
Feed (direct addition)	0–121
Functional feed (after refinery)	NA
Chemicals	114–606
Biofuels	3–30

Source: [117]

The estimated production cost (1.2 €/kg.dw) is still considerably higher to utilize seaweed as a biofuel feedstock (target value of feedstock price for biofuel production: 3–30 € per ton DM, see Table 8). However, technology can initially compete in the markets of high-value products such as hydrocolloid extraction (alginate market [116]). An initial focus on niche-markets (high-value products like protein, chemical, and hydrocolloid) and increasing the market value of sustainable seaweed might be a promising development pathway for commercializing seaweed cultivation in the North Sea region [124]; similar to PV module technology. Solar PV module technology initially focused on space applications due to their high cost. By tapping the learning opportunities in niche markets, the PV module technology achieved a drastic cost decline over the years.

Conversion Process (biofuel production): Seaweed does not contain lipids and is generally considered for its natural sugar and carbohydrates content, which can be digested into biogas or fermented into ethanol [114,125]. Other liquid products like biodiesel and bio-oils can also be produced using transesterification, liquefaction, and pyrolysis process; however, the low technology readiness level of these technologies limits the economic feasibility [126]. Each transformation pathway from seaweed to a biofuel product has different strengths and weaknesses [114]. This article focuses on anaerobic digestion (for biogas) and the fermentation process (for bioethanol) alone. Because both processes are highly matured in the market, and their end products are regarded as an alternative energy sources for transport, heating, and industrial sectors. In the anaerobic digestion process, factors, including high nitrogen content (unbeneficial carbon-to-nitrogen ratio), need for a physical or chemical treatment to break down the cell walls, and the presence of alkaline metals in the seaweed is considered to hinder the biogas production yield [127]. However, as a well-established technology in the market, anaerobic digestion offer possibilities to optimize the yields of biogas further, e.g., using co-digestion with straw or waste sludge to improve the production yield [128]. Production of liquid fuel requires suitable microorganisms that can ferment seaweed's different sugars (such as mannitol, alginate, laminarin) into ethanol and an energy-intensive drying process for the substrate [126].

Moreover, the literature dealing with the economics of biofuel production from seaweed is scarce compared to the literature dealing with the conversion process's technicalities. The available studies have commonly applied a bottom-up cost modeling methodology to investigate the economic feasibility of producing biofuels from seaweed. Also, no experience curve applications in projecting biofuel production costs (from seaweed) were found through this review. Roesijadi et al. [129]

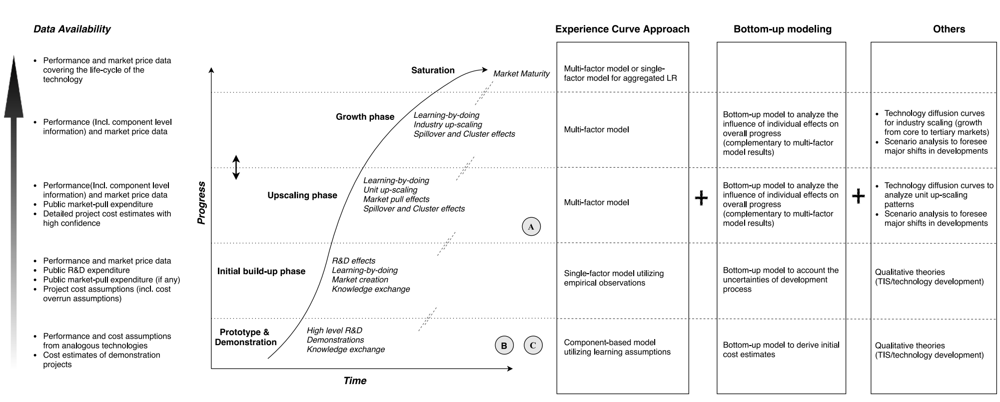

Fig. 11. Coherent framework to analyze the technological change process.

Table 9
Development status of offshore energy technologies – based on factual information from the review (at the time of writing this article).

Technology	Development Stage	*Brief Summary (from sub-section 5.1-5.3)*
Offshore Wind (A)	Upscaling Phase	• 23 GW of offshore wind capacity is installed worldwide by 2018 • Turbine rated capacity had increased from an average of ~3–4 MW in 1990–2015 to ~6–7 MW in 2015–2020, with 12+ MW turbines expected in the future [132]. • Increased offshore wind targets till 2030 from the UK (30 GW), DE (10.8 GW), DK (10 GW), NL (11.5 GW) [133] indicates the concurrent occurrence of the upscaling and growth phase of the technology.
Wave & Tidal Technology (B)	Prototype & Demonstration	• 26.8 MW of tidal stream and 11.3 MW of wave energy installations since 2010. • The tidal sector shows design convergence and has completed a series of successful demonstration projects. • The wave technology lacks design convergence. Currently, improving the reliability of the system is considered necessary.
Biofuel production from seaweed (C)	Prototype & Demonstration	• The practice of utilizing seaweed as feedstock for biofuel production is in infancy. • The estimated seaweed production cost is considerably higher than the target feedstock price for biofuel production. • The biofuel conversion technologies pose challenges for the use of seaweed as a feedstock. However, these technologies are relatively matured to offer possibilities to improve biofuel yields further.

analyzed the economics of biofuel conversion processes and reported the maximum allowable feedstock price for ethanol fermentation and the HTL process (for gasoline or diesel fuel), which is approximately 23 €/ton.dw and 5 €/ton.dw (1 USD = 0.82 EUR). Dave et al. [130] made a techno-economic assessment of electricity generation from biogas, with seaweed as a feedstock. The study assumed the seaweed production cost to be 50 €/ton.dw and estimated the breakeven electricity-selling price as 120 €/MWh. Soleymani et al. [131] compared the economics of biogas and ethanol production from seaweed, and stated that the by-products of the ethanol fermentation process (e.g., fertilizers) make bioethanol production competitive comparing to the biogas production (where the process residuals are only animal feed).

In summary, seaweed has inherent advantages that make them environmentally sustainable compared to previous generation biomass, but the practice of producing biofuels from seaweed is still in infancy. The key bottleneck in realizing a successful supply chain of biofuel production is the high production cost of seaweed. The conversion processes (anaerobic digestion and fermentation), on the other hand, pose some technical limitations, but they are relatively matured in the market to offer a range of possibilities to optimize biofuel yields further. Increasing the scale and efficiency of the cultivation process, co-cultivation with other aquaculture practices (e.g., mussels), sharing infrastructure costs with wind farms, and innovations to reduce the cost of plant materials are some of the identified factors that can lead to the reduction of seaweed production costs. The attractiveness of seaweed as a biofuel feedstock primarily lies in materializing the cost reduction efforts mentioned above and bringing the feedstock cost below 30 €/ton.dw.

5.4. Methodological recommendations

The literature review in the previous sections revealed that past studies commonly utilized the experience curve approach and bottom-up cost modeling methodology to project the future cost trends of offshore energy technologies. The applications of the experience curve approach were primarily aggregated (using SFEC model), which has led to an overview of the role of distinct learning mechanisms (LBS, LBD, scale effects) and factors (market dynamics, cost overruns, site-specific parameters) influencing the technology cost developments, e.g., see Fig. 6 and *section 5.2*. To overcome those limitations in future analyses and anticipate the process of technological change effectively, we propose a coherent framework based on this review's findings, refer to Fig. 11.

The framework first describes the energy technology innovation process in multiple stages and maps the expected data availability and typical characteristics of each development stage (adapted from the discussion in *section 3.1*). Then, acknowledging the expected data availability in each stage, the different forms of experience curve models that can disaggregate and quantify the individual learning effects are recommended (from Table 1). Finally, three other relevant methodologies that can be applied in tandem with experience curve models to overcome their limitations are suggested in the framework. These methodologies include bottom-up cost modeling, technology diffusion curves, and qualitative theories in the technological change process (refer to *Section 4.1*).

The markings A, B, and C in Fig. 11 represents the current development status of three offshore energy technologies, based on the summary shown in Table 9.

A (Offshore wind technology)

Step 1: Offshore wind technology is well established in the market and offers excellent data availability, compared to other emerging technologies. So, the initial step is to utilize the multi-factor experience curve model (Eqn. (8)) and quantify the influence of individual learning effects on the technology's overall cost developments. Here, the term technology cost refers to both investment cost and LCOE of offshore wind.

$$C_t = C_0 * \prod_i X_{i,t}^{-E_i} \tag{8}$$

$$where\, i = \{cuml.capacity, R\&D expense, market-pull expense, scale parameter\}$$

Data needs for the experience curve model (Eqn. (8)) include wind farm investment cost (€), LCOE (€/MWh), cumulative installed capacity (MW), cumulative electricity generated (MWh), R&D expense (€), market-pull expense (from subsides like FIT, CfD contracts) and scale parameter (unit & industry level). The experience curve model outcomes will provide quantitative accounts of individual learning effects, including LBD, LBS, and scale effects. However, a couple of limitations to consider here, a) cost overruns and external market dynamics could influence the available project price data from the early commercialization period. Further analysis is suggested to interpret the impact of these effects on expected LR outcomes, as shown in Table 2 b) In an ideal case, all the data requirements mentioned above will be available. So, apply a bottom-up cost modeling methodology (as step 2) to break offshore wind's overall progress into component-level developments.

Step 2: Offshore wind is a complex system, and varying technological and site parameters influence the technology's total cost. To quantify the component-level developments and the impact of those technological parameters on offshore wind cost, utilize bottom-up cost modeling methodology, and derive cost breakdown of offshore wind over periodic intervals. Here, it is crucial to interpret the outcomes of the multi-factor experience curve model (individual learning effects) and bottom-up assessments (component-level achievements) as complementary to identify the sources of cost reduction for offshore wind technology.

Furthermore, to obtain additional insights on the growth dynamics (unit-upscaling pattern & market growth) of offshore wind in the market, the available unit- & industry-scaling parameter data can be fitted using logistic growth curves [40]. The first two steps dealt with analyzing the past achievements of the technology. The future outlook is discussed in the next step.

Step 3: The key limitation of the experience curve approach is that it could not foresee radical changes in the development process. So, it is suggested to derive the future outlook of offshore wind in terms of possible futures, i.e., scenarios. Currently, offshore wind technology is identified to be in the upscaling phase of its development process. The base scenario of offshore wind is business as usual, where the unit upscaling of the technology continues until its saturation levels and technology diffuses to the secondary and tertiary markets, i.e., market growth. Future cost trends under the base scenario can be derived by extrapolating the multi-factor experience curve model's outcomes from step 1, where the influence of individual learning effects is quantified separately.

For other scenarios, i.e., to analyze the impact of radical changes on the overall cost developments or analyze the developments of design variants, the combined use of the bottom-up cost modeling approach is suggested. Floating offshore wind technology utilizes floating foundations (spar-buoy, spar-submersible, or tension leg platform), instead of fixed-bottom-structures, to capture wind energy in the deeper water areas (water depth >60 m). The cost of floating offshore wind technology can be estimated by utilizing the component-level cost assessments (except foundations) from step 2 and floating foundations' cost information. Then, the developments can be extrapolated as a scenario by considering these two factors. First, the floating foundation is a relatively new entrant in the offshore wind market (building on existing experience from the oil & gas industry), and there are limited empirical data available related to the cost of floating foundations. So, the assumptions on the development trend of floating foundations should be based on robust engineering assessments b) the choice of foundation (fixed-bottom or floating) impacts other technology components like the cost of installation, O&M expenses, electrical infrastructure, capacity factor (higher windspeed in deeper waters) and cost of capital (risks). It is recommended to account for these factors to avoid overestimating floating offshore wind technology's development potential.

B (Wave & Tidal technology)

Step 1: Both wave & tidal technology are identified to be in the prototype & demonstration stage of the development process, where the availability of technology data is limited. So, using a component-based experience curve model is recommended as the first step to estimate the future investment cost trends (Eqn. (9)).

$$C_t = \sum_{i=1}^{n} C_{0,n} X_{n,t}^{-E_n} \tag{9}$$

n in the equation refers to the n number of technology components.

The experience curve model equation expresses the total investment cost of wave & tidal technology as the sum of its components cost, which comprises civil and structural, mechanical equipment supply and installation, electrical supply and installation, indirect project costs, owner costs (Fig. 8).

The two inputs needed for the component-based experience curve model are.

a) *Initial investment cost estimates ($C_{0,n}$)* – Utilize bottom-up cost modeling methodology to estimate the initial technology cost of wave & tidal technology. The cost of the demonstration projects can also be used here as initial cost, but a direct extrapolation of technology costs from prototype capacity to a commercial-scale capacity should be interpreted with caution (scaling uncertainty).
b) *Learning rate inputs for technology components (E_n)* – As mentioned earlier, both wave & tidal technology are in the prototype & demonstration stage of its learning process with limited data availability. So, the learning rate inputs for subsystems are referred from analogous technologies in the literature, including existing marine engineering practices like the oil & gas industry and offshore wind (e.g., Table 6).

By applying the learning rate and initial cost inputs to each subsystem (in Eqn. (9)), the total technology cost of wave & tidal is estimated based on increased cumulative installed capacity. The investment cost projections can also be translated in the LCOE by assuming OPEX, project lifetime, cost of capital, and decommissioning expenditures. Later, the projected cost estimates can be fitted in a single factor experience curve model to obtain an aggregated LR. The merit of the component-based experience curve model allows the cost of individual technology components to change at a rate reflecting its maturity in the market. In the next two steps, the uncertainty of wave & tidal technology's future cost trends is discussed.

Step 2: As a compound energy system intended to be deployed and operated in harsher marine conditions, both wave & tidal system is likely to experience cost overruns during the early commercialization phase. To avoid overestimating the development potential of the wave & tidal technology, assume a minimum installed capacity (as initial deployment level in Eqn. (9)) where cost overruns are controlled, and cost reductions are likely to begin [23].

Step 3: The initial technology cost and deployment level assumptions in the experience curve model (in Eqn. (9)) influence the LR estimates and cost development trend significantly [74]. Conduct a sensitivity analysis by varying these assumptions in Eqn. (9) and examine the impacts on LR estimates of the wave & tidal technology. The sensitivity analysis is specifically crucial for wave technology, as the available initial investment cost estimates are highly uncertain due to the lack of design convergence.

C (Biofuel production from seaweed)

Step 1: Biofuel production from seaweed involves a value chain of processes from seaweed cultivation to biofuel conversion. The practice of seaweed cultivation is in infancy in the North Sea region. So, using a component-based experience curve model is recommended as the first step to estimate the future cost trends (Eqn. (10)).

$$C_t = \sum_{i=1}^{n} C_{0,n} X_{n,t}^{-E_n} \tag{10}$$

n in the equation refers to the n number of technology subsystems.

The experience curve model equation expresses the biofuel production cost (Levelized cost of biofuel) as the sum of its technology subsystems cost, which comprises feedstock production and biofuel conversion system (refer to section 5.3).

The two inputs needed for the component-based experience curve model are.

a) *Initial cost estimate ($C_{0,n}$)* - Utilize bottom-up cost modeling methodology to estimate the initial cost of biofuel production from seaweed [122,131].
b) *Learning rate inputs for subsystems (E_n)* - Seaweed cultivation at a large-scale is an emerging practice in the EU region. However, there are existing practices for seaweed-based food production and hydrocolloid extraction. The available price, and cumulative production information of seaweed (Data source: [134]) can be utilized to derive an empirical LR for seaweed production cost. The conversion processes (anaerobic digestion and fermentation), on the other hand, are relatively well-established technologies in the market, and the LR estimates can be directly referred from the existing literature [135,136].

By applying the LR and initial cost to each technology subsystem (in Eqn. (10)), the biofuel production cost is estimated based on increasing cumulative output for increasing cumulative output levels is estimated. Later, the cost estimates can be fitted in a single-factor experience curve model to obtain an aggregated LR.

The key advantage of the component-based experience curve approach here is that it allows the subsystems' cost to change at a rate reflecting its maturity in the market, i.e., accounts for the differences in the market maturity between seaweed cultivation and biofuel conversion processes here. The uncertainty of the future cost trends of biofuel produced from seaweed is discussed in the next step.

Step 2: As discussed in section 5.3, the production cost of seaweed is unclear due to limited commercial experience in the EU region, and also, a little consensus is found among the outcomes of cultivation trials. Besides, seaweed production cost depends on several technical factors, including scale, cost of plant material, yield, and infrastructure cost. These parameters' initial assumptions can highly influence the future cost trends of biofuels produced from seaweed in the component-based experience curve model. To quantify their impacts, conduct a sensitivity analysis by varying the initial seaweed production cost assumptions in Eqn. (10). A range of initial production cost estimates can be derived using the bottom-up cost model [122], e.g., base-case, highly-optimistic scenario (low production cost), and worst-case scenario (high production cost). Then, apply these assumptions in the component-based experience curve model equation and project a series of cost development scenarios, indicating the uncertainties of the future cost trends.

6. Conclusion

This article has reviewed a large volume of literature on the experience curve approach theory, its applications, and uncertainties. The review has provided a systematic overview of the different forms of the experience curve models, their advantages and limitations in analyzing the technological change process, and how to address those limitations when projecting technology cost developments. Finally, as a case study, the developments of three offshore energy technologies were reviewed, and the applications of the experience curve approach in predicting their technological developments were examined.

The first part of the conclusion summarizes the key insights gained from the review of the experience curve approach, and then, the suggestions for future analyses foreseeing the developments of offshore energy technologies are outlined.

6.1. Insights from the review of the experience curve approach

Technological change, in general, is a complex process that involves several stages and diverse characteristics. At each stage, a combination of learning mechanisms influences the technology's progress; LBD, LBS, and scale effects are the most common ones. To quantify these effects separately in the experience curve approach, a high level of data characterizing these learning mechanisms is essential, as experience and performance metrics (refer to Table 1). However, in practice, data related to specific experience metrics such as R&D expenditure are not publicly available or readily accessible, which has been a significant barrier for the applications of multi-factor experience curve models. Otherwise stated, the data unavailability is a common rationale behind the prevalent use of the SFEC model in the literature.

The risk of not separating the learning effects using the multi-factor experience curve model (put differently, the risk of overestimating the development potential of the technology in the SFEC model, refer to section 4.4) depends on the nature of the technology itself. Technologies like PV modules are commonly referred to as modular technologies, which benefit cost reduction majorly through production and use. The SFEC model was able to describe the relation (negative correlation) between cumulative output and technology cost well for such technologies (see examples in Refs. [18,27]). Technologies like offshore wind and coal power technology, on the other hand, are compound energy systems and typically exhibit stronger unit scale economies, in addition to experience gain through production and use (as discussed in section 3.1). Here, it necessary to separate the learning effects and identify the sources of technology cost reduction using multi-factor models. Because the cumulative output of the technology alone as an explanatory variable in the SFEC model was not adequate to explain the observed cost developments, refer to the case of offshore wind in Fig. 6.

Besides the choice of experience curve model, several uncertainties in the experience curve analysis were identified, including the limitations of the approach, how the presence of market dynamics, cost overruns, and changes in data periods influences technology's LR outcomes. A detailed discussion on how to identify these influences, isolate/interpret their impacts on the LR estimates is provided in section 4. A key recommendation here is that future studies employing the experience curve approach should move from deterministic LR reporting to a distributional approach by conducting sensitivity analysis. For instance, derive a range of LR estimates by varying the data periods (e.g., analysis in Table 2) and explanatory variables (quantify the individual learning effects using multi-factor experience curve models, as indicated in Fig. 11). This practice will improve our understanding of the factors influencing the cost developments observed in the technology and also inform the uncertainties associated with using the observed learning rates to anticipate future cost developments.

6.2. Methodological recommendations to analyze the developments of offshore energy technologies

The literature review reveals key limitations of the experience curve approach, including incapacity to foresee radical changes in technology developments and difficulties in separating the learning effects due to data unavailability (see section 3.1). The impacts of these limitations were observed in the outcomes of the past studies analyzing the developments of three emerging offshore energy technologies, i.e., aggregated application of experience curve application resulted in the oversight of factors influencing the observed cost developments (see sub-section 5.1–5.3). To overcome these limitations in future analyses, we proposed a coherent framework in projecting the process of technological change (Fig. 11) and applied it to the case of three offshore energy technologies (sub-section 5.4). The summary of the recommendations is provided below, *Offshore wind technology* has shown a unique development trend where the investment cost and LCOE have steadily increased between 2000 and 2013, and after that, a sharp decline is observed. Scale effects, site-specific characteristics, input material prices, market competition, cost of capital, and capacity factor improvements have been attributed to such a development trend; however, modeling their influences is still a work in progress. Therefore, as an initial step, using a multi-factor experience curve model and a bottom-up cost modeling approach is recommended. The multi-factor experience curve model will separate individual learning effects, and the bottom-up cost modeling approach will breakdown the overall developments into component-level achievements. These outcomes will give a clear account of the sources of cost developments observed for offshore wind. Then, for the future outlook, it is suggested to derive the cost projections in terms of scenarios. Specifically, to overcome the limitations of the experience curve approach in foreseeing the impact of radical changes/technological variants on overall cost developments. Under the base case scenario, the future cost trends can be derived by extrapolating the multi-factor experience curve model's outcomes. For other scenarios, the bottom-up cost modeling approach will provide flexibility in accounting for these radical changes in offshore wind cost developments.

Wave & Tidal technology and biofuel production from seaweed are at the beginning of its development process. The availability of data is limited at this stage to derive empirical LR's specific to those technologies. So, using a component-based experience curve model is recommended, where learning experiences from the analogous technologies can be referred to derive future cost trends. For wave & tidal technology, the learning experiences can be referred from existing marine engineering practices like the oil & gas industry and offshore wind (see Table 6). On the other hand, the value chain of biofuel production from seaweed includes a mix of emerging practices (seaweed cultivation) and matured technologies (fermentation and anaerobic digestion). To derive an empirical LR specifically for seaweed production cost developments, refer to the existing seaweed supply chains (see Ref. [134]) such as seaweed-based food production, hydrocolloid extraction. For biofuel conversion technologies, the LR estimates can be directly referred from the recent literature as they are well-established in the market. Lastly, it is critical to quantify the uncertainties of the initial technology cost and deployment level assumptions on technologies' future cost trends.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Technological progress and cost reduction have been commonly dealt within these three research fields.

1) Endogenous growth theory
2) Innovation theory
3) Experience curve approach.
1) Endogenous growth theory holds that economic growth is primarily the result of endogenous forces and not external forces. The simple AK model says that the production is dependent on knowledge, a function of physical capital. However, critics argue that endogenous growth models are challenging to validate through empirical evidence.
2) Innovation theory has evolved from an over-simplified linear model (supply-push or demand-pull perspective) that explains the innovation processes to a more complex system perspective approach that emphasizes the importance of knowledge flows between actors, institutional changes, political and regulatory risks in the innovation process. Technological innovation systems approach (TIS) is considered as one of the most developed innovation theories, which has been commonly applied to study the innovation process in the field of low-carbon energy systems. Nevertheless, innovation studies offer more contextualized qualitative insights into the innovation process than quantitative accounts.
3) The experience curve approach relates the accumulated experience of a technology or a product to the cost developments in a single quantitative parameter called the Learning rate. The approach is said to provide some degree of empirical evidence for experience-based cost reduction. For such reasons, the experience curve has become one of the widely-adopted methodologies to anticipate cost developments across several sectors.

Appendix B

A database comprising the investment cost and technical characteristics of the offshore wind farms is compiled, using the data available from the past studies [91,137,138] and web databases [139,140]. The scope of the database covers the commercial offshore wind projects fully commissioned and operating in Germany, Netherlands, Denmark, Belgium, Sweden, and the UK, between the period 1991–2019. Currently, the investment costs of projects between different countries should not be compared directly (data in Fig. 6) because each country has adopted different regulations for offshore transmission and site developments (i.e., whether the project developer incur the costs or it is incentivized). So, the data points in the figure should be considered for interpreting the overall cost development trends alone. The regulatory differences and their influences on the cost developments will be addressed in future analyses.

The inflation effects in the investment cost data are corrected using the Harmonized Index of Consumer Prices (HICP) of the Euro area, and all project costs are represented in 2015 EUR real values. Fig. 6 in the article compares the actual offshore wind farm investment costs (realized) and the outcomes of past studies (projections). Experience curve results (LR) from the past studies have been translated into cost projections using the actual cumulative installed capacity of offshore wind technology (Fig. B. 1), as per the equation shown below,

$$Cost_{year\ t} = Cost_{year\ 0} * (Cumulative\ installed\ capacity)^{-E}_{year\ t} \quad (C.1)$$

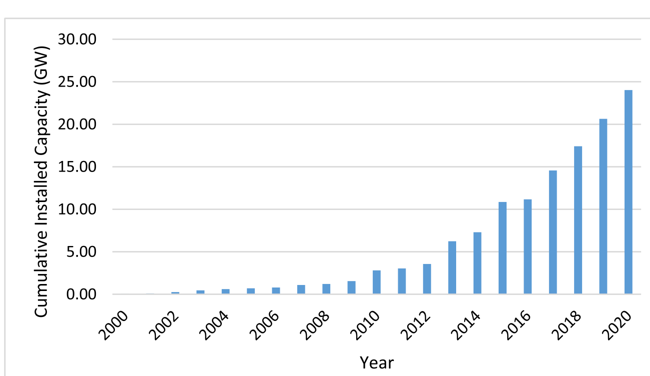

Fig. B.1The cumulative installed capacity of offshore wind (DE, NL, DK, BE, SE, UK).

Additional notes relevant to Fig. 6

- JRC estimate proRES scenario (1) - projections for wind farms with monopile foundations and deployable at a medium distance to shore.
- JRC estimate proRES scenario (2) - projections for wind farms with jacket foundations and deployable at a medium distance to shore.
- EWEA projection: the cost increase projected till 2010 reflects the absence of economies of scale, low market development, bottlenecks in the supply chain, and few offshore turbine suppliers.

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