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The potential of marine energy technologies in the UK – Evaluation from a systems perspective

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A R T I C L E I N F O

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A B S T R A C T

Accelerated technological change plays a crucial role in enabling the low-carbon energy transition. Quantitative energy modelling exploring alternative long-term decarbonisation pathways can support policy-makers in choosing the most important areas for technology promotion. This study analyses the potential contribution of marine energy in the UK from an energy systems perspective considering the trade-offs between local lead markets and global learning, the uncertainty in the learning potential, competition with alternative technologies and impacts on system balancing. The results indicate that only under very favourable conditions, i.e. with learning rates above 15% and high global deployment, marine energy will have a significant contribution to the UK decarbonisation pathway. Alternatively, marine energy could constitute a hedging strategy against multiple failure in other low-carbon options. The early strategic investments into marine energy lead, in most cases, to a slight rise in societal welfare costs compared to the respective cases without attempts to induce marine learning and brings benefits to the electricity system. Thus, on the whole, we conclude that marine energy has the potential to contribute to the UK energy system, but there is a substantial risk that strategic investments in a national lead market will not directly pay off in the long term.

1. Introduction

The recent Paris agreement [79] has put further emphasis on the substantial decarbonisation challenge that nations will face in the coming decades. To enable such deep emission cuts, accelerated technological change will be required, as most low-carbon technologies still have the potential for considerable cost reductions [12]. Governments can play an important role in spurring technological innovations by implementing measures of technology promotion that go beyond the standard instruments of climate policy like emission taxes or trading systems. Such additional support for sustainable technologies is justified by the simultaneous occurrence of two market failures – environmental externalities as well as knowledge and other externalities in the innovation system [35]. The question then remains, however, what government intervention in innovation systems should look like – whether only general support to promote a strong national innovation system or explicit support for the development, demonstration and diffusion of specific technologies should be provided [27,51]. A look at the current climate and energy policy landscape in Europe reveals that governments strongly intervene in innovation systems and use both technology-push and demand-pull mechanisms to promote low-carbon technologies [18,63]. When deciding on the right areas and measures for technology promotion, governments also have to take national vs. global trade-offs into account [54]. In most cases, learning in energy technologies takes place in global markets and national energy systems can benefit from spill-overs [42]. At the same time, the national framework conditions (the innovation system, natural conditions, regulations, etc.) play a crucial role in the adoption and diffusion of new technologies. Moreover, the possibility for national niche markets and potential economic benefits from first-mover advantages have to be taken into account, as has been the case for the wind industry in Denmark, Germany and the Netherlands. [46,86]. In addition, with the need for a rapid low-carbon transition of the energy system becoming ever more urgent, technologies need to reach commercial availability soon. Here, a statement from the UK's Carbon Plan [16], defining the long-term national decarbonisation strategy, is striking: *"In the 2020s, we will run a technology race, with the least-cost technologies winning the largest market share. Before then, our aim is to help a range of technologies bring down their costs so they are ready to compete when*

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the starting gun is fired." [16]; p.1).

Marine technologies could represent an important part of a low carbon energy system [37]. The UK is currently in an advantageous position to establish a national lead market for marine (wave and tidal) energy technologies having favourable natural conditions [9]. Globally, the UK is leading in terms of planned ocean power projects and number of major industry players as can be seen in Fig. 1. Additionally, the UK has several world class sea testing facilities and benefits from a variety of public funding mechanisms, including the Offshore Renewable Energy Catapult and a strike price between 300 and 310£/MWh for wave energy and 295–300£/MWh for tidal energy for 2021/22 and 2022/23 respectively, under the Second Contract for Difference (CdF) Allocation Round taking place in April 2017 [20]. For further information on the development landscape for marine energy in the UK, see Refs. [22,38,44]. At the same time, marine technologies are still at an early stage of development and lagging behind other more established renewable energy technologies. Thus, further government support would be needed to arrive at a dominant technology design (especially for wave), implement full scale testing, perform environmental assessments, develop and optimise methods for installation, operation & maintenance as well as grid connection and, above all, to drive down costs [22,44].

In the analysis at hand we develop an exogenous learning approach for marine technologies in a national energy system, paying special attention to *global vs. local trade-offs and uncertainty.* We analyse the interplay between strategic investments into a national lead-market in the medium-term and spill-overs from global technological change in the long-term and apply a sensitivity analysis on key learning parameters. Furthermore, the contribution of marine technologies in the case of failure of other low-carbon electricity options is explored. With this approach we address the question under which conditions marine energy could be expected to have a significant contribution to the UK decarbonisation pathway and whether an early UK action could be justified as cost effective for the UK, if it then triggered further global deployment, and learning, later on.

Quantitative energy modelling has long played a key role at the science-policy interface by mapping out possible decarbonisation strategies and relaying these insights to policy-makers [78]. Bottom-up, cost optimizing whole energy system models are applied to determine cost-efficient and consistent long-term pathways for a low-carbon energy transition and to analyse interactions and the competition between technologies as well as low-carbon energy vectors in the system. Given the complexity of innovation and learning processes, most energy system analyses make exogenous assumptions on the rate of technological change [67]. Also, in system analyses for small open economies it is usually reasonable to assume at least part of the learning process as exogenous and taking place on the global scale. Endogenous approaches usually focus on learning-by-doing potentials, where investments costs (or other technology parameters) improve as a function of the cumulative installed capacity according to a specified learning rate, so-called one-factor learning curves [8]. A variety of aspects of the learning process have been analysed with energy systems models including component learning [1,58,82], the impact of technology clusters [19,43,75], regional spill-overs [6,31,54,72], the effect of R&D expenditures through two-factor learning curves [7,47,55,56,83] as well as learning under uncertainty [28,73]. Concerning marine energy technologies a number of studies have reviewed the current technology designs [5,26,48], performed economic assessments [2,4,14,40], analysed the learning potential and prospects of marine technologies [21,52], and assessed key investment barriers [45,50,57]. There are only two studies which look at marine learning from an energy systems perspective [37]. have performed a first assessment of marine energy in the UK with a systems approach setting up scenarios with combinations of learning for different technologies. Their analysis does not investigate the impacts of alternative learning rates or differentiate between local and global learning, nor does it analyse the impacts technology failures for other key technologies might have on the prospects of marine. Sgobbi et al. [87] assess the effects of decreasing costs due to global technology learning and of efficiency improvements for marine technologies on their deployment in the EU. This study does not analyse local learning or assess how marine deployment may depend on the success or failure of other technologies.

The cost-effective deployment of marine technologies depends on the respective learning on the national and global level as well as on the developments in other technologies. Our literature review highlights that no previous study has systematically explored how the interplay between changing key marine learning parameters, both nationally and globally, and the failure and success of competing technologies affects the modelled deployment of marine energy. We close this gap by using a long term energy systems model to assess 80 different scenarios with varying parameters on national and global marine learning, technology availability of low carbon electricity options and also technology spill-overs between marine and offshore wind. This allows us to determine the conditions under which marine energy can, in our model, become part of the energy system. In addition, we soft-link UKTM to a high spatial and temporal resolution electricity system model to assess one other aspect of the potential system benefits offered by marine power. In addition to providing information about the possible required thresholds for marine technology breakthrough, this

Current marine power projects [MW]

	Installed capacity	Consented projects
UK	**9.3**	**136.0**
Canada	20.0	20.5
China	4.4	7.6
US	-	2.7
Rest of the world	4.3	37.8
TOTAL	**38.1**	**204.5**

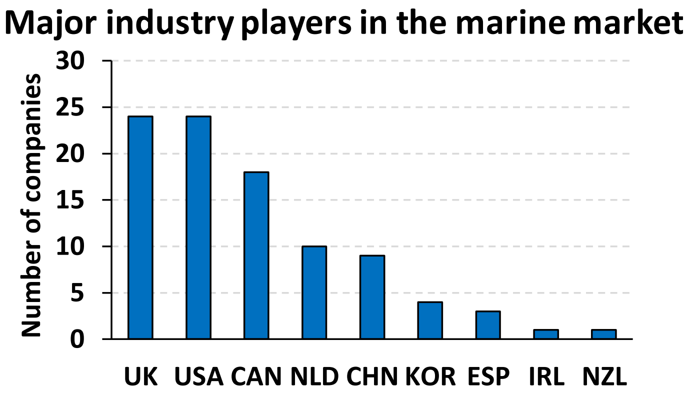
Major industry players in the marine market

Fig. 1. Key market figures for marine technologies in 2014 (Source [64]).

article contributes to the literature on the role of technology learning in long term decarbonisation strategies.

The rest of this paper is structured as follows. The next section focuses on the methodology, providing a short overview on the whole energy systems model and the approach for the learning sensitivity analysis. In the third section, the results of the analysis are presented, including the additional analysis on electricity system impacts. The implications on the benefits and costs of developing a national lead market for marine technologies in the UK are further discussed in section 4. The paper concludes which a short discussion of future research needs.

2. Methodological approach

2.1. Economic evaluation from a whole energy systems perspective

2.1.1. The national energy system model UKTM

For the system analysis of learning in marine technologies the new national UK TIMES energy system model (UKTM) is employed [15,23,24]. UKTM has been developed at the UCL Energy Institute over the last two years as a successor to the UK MARKAL model [88]. It is based on the model generator TIMES (The Integrated MARKAL-EFOM System), which is developed and maintained by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA) [49].

UKTM is a technology-oriented, dynamic, linear programming optimisation model representing the entire UK energy system from imports and domestic production of fuel resources, through fuel processing and supply, explicit representation of infrastructures, conversion to secondary energy carriers (including electricity, heat and hydrogen), end-use technologies and energy service demands. Generally, it minimizes the total welfare costs (under perfect foresight) to meet the exogenously given, but price elastic, sectoral energy demands under a range of input assumptions and additional constraints, thereby delivering a cost optimal, system-wide solution for the energy transition for the coming decades.

A key strength of UKTM is that it represents the whole UK energy system under a given decarbonisation objective, which means that trade-offs between mitigation efforts in one sector versus another can be explored. The model is divided into three supply side sectors (resources & trade, processing & infrastructure and electricity generation) and five demand sectors (residential, services, industry, transport and agriculture). All sectors are calibrated to the base year 2010, for which the existing stock of energy technologies and their characteristics are known and taken into account. A large variety of future supply and demand technologies are represented by techno-economic parameters such as the capacity factor, energy efficiency, lifetime, capital costs, O&M costs etc. Assumptions are also exogenously provided for attributes not directly connected to individual technologies, such as fuel import prices, resource availability and the potentials of renewable energy sources. UKTM has a time resolution of 16 time-slices (four seasons and four intra-day times-slices). In addition to all energy flows, UKTM tracks CO_2, CH_4, N_2O and HFC emissions. For more information on UKTM see Ref. [25].

In addition to its academic use, UKTM is the central long-term energy system pathway model used for policy analysis at the Department of Energy and Climate Change (DECC) and the Committee on Climate Change (CCC).

2.1.2. Methodology for the sensitivity analysis around technology learning

UKTM explicitly models, in a system context, the competition between different technologies that provide the same fuel or energy services. Here, this approach is used to explore the potentials of marine technologies to contribute to the decarbonisation of the UK energy system and the potential benefits and costs from the strategic development of a national market for wave and tidal technologies in the UK. Special attention is paid to potential learning-by-doing effects and the interplay between national and global technology development. The following framework for marine technologies is set up: based on its current position in the marine market, it is assumed that the UK undertakes, with the help of targeted government support, a strategic development of the national marine energy market and establishes itself as the market leader by 2030. In this time, learning effects depend solely on the national cumulative capacity instalments, reflecting the niche market development taking place in the UK. After 2030, the global deployment of marine technologies is expected to pick up such that further learning occurs fully on the global market. Further, marine technologies no longer receive any preferential treatment in the UK.

This storyline is then implemented in UKTM in the following manner (see Fig. 2). Given the current uncertainties around the technology design that will prevail in the long term, marine technologies – representing both tidal stream and wave power – are modelled by one process in UKTM.[1] The initial capital costs of 6000 £/kW are based on [22]. The resource potential is adopted from Carbon Trust (2011), resulting in a maximum capacity for wave and tidal stream technologies of 24.5 GW in the UK. The strategic national market development between 2020 and 2030 is reflected in the model by forcing in a trajectory for installed capacity of this marine technology, reaching 0.5 GW in 2020 and 4 GW in 2030 (based on projections from Ref. [69]. Assessing learning-by-doing for technologies that are not yet fully commercial is challenging (see e.g. Refs. [71,74] for fuel cells). So far, little investments in marine have occurred in the UK and with lead times of 3–5 years the expansion and early stage cost reductions that can be expected to take place until 2020 are limited. We therefore parametrize the learning-by-doing process to start in 2020, with an initial capacity of 0.5 GW and an initial investment cost of 6000 £/kW (based on [22,52]). All learning effects are calculated outside of the model - assuming that each doubling of cumulative capacity additions leads to a reduction in the specific investment costs determined by the learning rate - and the resulting cost trajectory is then fed into the model. Hence, in the period from 2020 to 2030, the assumed learning rate (see below) is applied to the national cumulative capacity additions. After 2030, no further national investments are forced into the model, such that marine technologies are in direct competition with the other low-carbon electricity options in UKTM and the model chooses the cost optimal investments for fulfilling the energy demands. In addition, from 2030 onwards the learning effects are based on the expected global cumulative deployment of marine technologies and assuming that the UK benefits from full regional spill-overs (i.e. technology costs are determined also for the UK based on the global cumulative deployment of the technology).

Starting from this basic approach, a sensitivity analysis is then conducted on key developments that affect the competitiveness of marine technologies in the UK (Table 1). The learning rates for marine technologies, that are both applied to the national learning between 2020 and 2030 and to the global learning afterwards, are varied between 5 and 20%, based on what has been observed for other electricity technologies in the past [41,60,77] and what is generally expected for marine technologies [4,9,36]. Apart from the

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[1] Tidal barrages are modelled separately in UKTM, but are not included in the learning approach as they constitute a very different technology compared to wave and tidal stream [33].

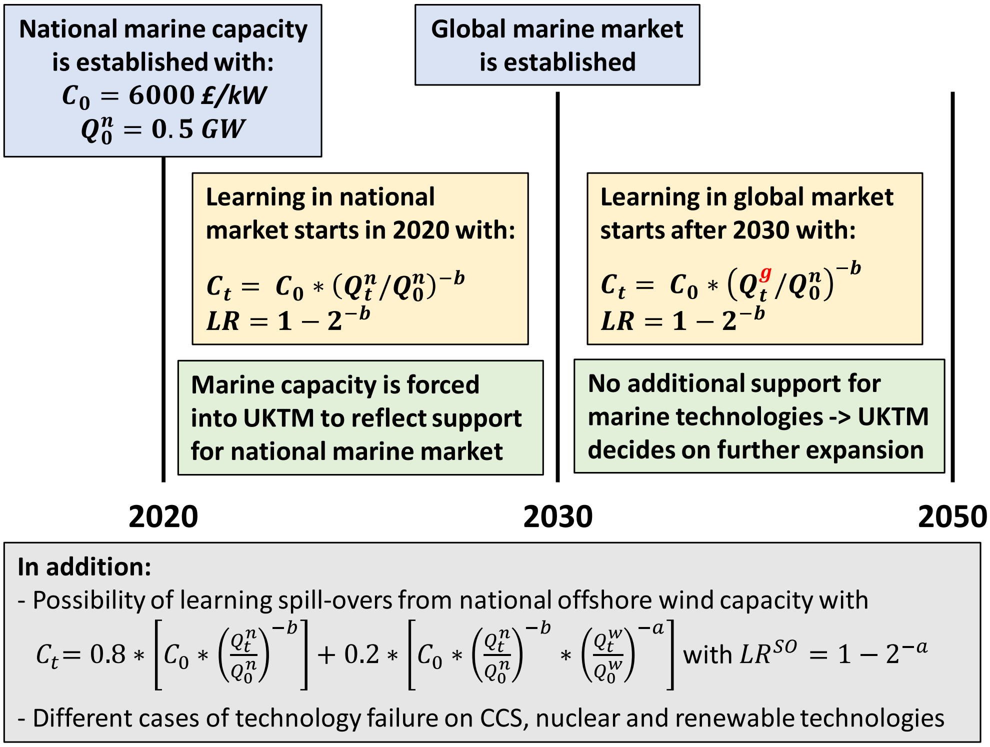

Fig. 2. Graphic representation of the basic modelling approach with the standard learning by doing equations with.

Table 1
Overview on parameters varied in the sensitivity analysis.

Learning rate	5%, 10%, 15%, 20% (both national and global)
Global deployment after 2030	- High: 178 GW in 2050 (based on 2° scenario in ETP (2015)) - Low: 37 GW in 2050 (based on 6° scenario in ETP (2015))
Failure in other technologies	- NO CCS (CCS does not become available in the UK) - Low NUC (total nuclear capacity is restricted to 16 GW) - Low RE (installed capacity restricted to 16 GW for offshore wind and 10 GW for solar PV) - Combined (all of the failures combined)
Learning spill- overs (yes/no)	Partial spill- over from installed offshore wind capacity: Conservative learning rate of 7%, learning in 20% of total capital costs (installation and connection) and 50% of O&M costs

learning rates, the push for marine technologies on the global level will strongly affect their competitiveness in the UK in the long-term, since national capacity investments alone are unlikely to induce sufficient cost reductions. In the present sensitivity analysis, a high and a low trajectory are contrasted, both taken from the IEA's *Energy Technology Perspectives 2015* [32] with a gradual increase of global marine capacity to 37 GW (business-*as*-usual/6 °C Scenario) or 178 GW (2 °C Scenario) until 2050. Furthermore, the contribution of marine technologies in the case of failure of other low-carbon electricity options is explored with four different cases in addition to the scenarios with the standard UKTM assumptions on technology availability: (1) CCS technologies do not become commercially available in the UK before 2050 (case "No CCS"); (2) nuclear capacity is restricted to 16 GW, i.e. only a moderate increase over the currently installed 11 GW, while the reference case assumes a nuclear potential of 33 GW in line with [16] (case "Low NUC"); (3) the extension of key renewable electricity options is restricted with an installed capacity of 16 GW in the case of offshore wind (based on current projects with planning permission [70]) and 10 GW for solar PV [59], while in the reference case considerably higher technical potentials are assumed (case "Low RE"); (4) a combination of the technology failures in cases 1–3 (case "Combined"). Finally, the potential for learning spill-overs (SO) from the national offshore wind capacity are taken into account. Given the shared environment, marine and offshore wind face similar challenges, especially in terms of installation and grid connection as well as operation and maintenance. Thus, the potential for partial spill-overs from the national cumulative offshore wind capacity is incorporated assuming that the part of the investment cost of marine technologies that are associated to installation and grid connection (assumed to be 20% based on [44] can benefit from increasing national offshore wind capacity. Also, 50% of the operation and maintenance costs can benefit from these partial learning spill-overs to reflect the shared environment. The spill-over effects are added to the model in an iterative manner: in a first run without SO, the cumulative national offshore wind capacity is calculated. Afterwards, the cost trajectory for marine technologies is adjusted in accordance with these partial SO. The model is run again to assess whether this has influenced the offshore wind capacity (and therefore the SO effects). The cost trajectory for marine technology is adjusted accordingly until the offshore wind capacity does not change from one run to the next.

In the sensitivity analysis, all possible parameter combinations are explored resulting in 80 scenarios in total (4 learning rate cases

* 2 global deployment cases * 5 technology availability cases * 2 spill-over cases).

Apart from the assumptions for the sensitivity analysis described in Table 1 standard input parameters of UKTM are used in the scenario analysis. The demand drivers are based on standard socio-economic assumptions, most importantly an average GDP growth rate of 2.4% p.a [62]. and a rise in population of 0.5% p.a [65]. over the period from 2010 to 2050. For all other electricity technologies, exogenous learning rates are applied, assuming that the UK is a price taker for globally developing technologies. These cost trajectories are adopted from the Dynamic Dispatch Model (DDM) [17].[2] All scenarios take the UK legislation on GHG emission limits into account, comprising the four five-yearly carbon budgets that have been fixed so far until 2027 [10] and the long-term target of a −80% reduction until 2050 compared to 1990 [29]. To give the model flexibility with respect to the timing of emission reductions after the four carbon budgets, the long-term target is applied via a cumulative budget constraint covering the period from 2028 to 2050 which results in the same total quantity of emission reduction as would a linear reduction pathway to 80% until 2050.

3. Results

3.1. The impact of learning in marine technologies on the energy system

This section provides an overview on the results of the learning sensitivity analysis in UKTM focusing on the possible contribution of marine technologies to the UKTM energy system and on the cost implications of the strategic development of a national niche market for marine technologies.

3.1.1. The reference case

With the aim to establish a point of reference for the sensitivity analysis on learning in marine technologies, we first briefly present results on a reference case which has the same basic UKTM assumptions as the sensitivity runs, but does not include any learning on marine electricity technologies. Thus, this case indicates how the transition to a low-carbon electricity system in the UK could look like if no further development of the marine sector would take place (Fig. 3). As expected, the use of fossil fuels is strongly reduced, with a phase-out of coal until 2030 and a reduction of the contribution of natural gas to less than 20% (almost entirely with CCS). Based on the cost assumptions in the model, electricity generation in the UK would be heavily dominated by nuclear energy, the expansion of which in the model follows the imposed growth constraints. By 2050, the overall capacity limit of 33 GW is reached resulting in a contribution of about 50% to total generation. From 2030 onwards, the use of CCS is extended to biomass plants due to the potential to generate negative emissions and thereby reducing the pressure on the end-use sectors to contribute to emission abatement. Accordingly, the electricity system becomes zero-carbon in 2030 and delivers up to 50 Mt CO_2eq of negative emissions per year afterwards. Given the strong focus on large-scale technologies like nuclear and CCS, the expansion of renewable electricity generation is less strong with a share of wind energy in total electricity generation of 15% in 2050.

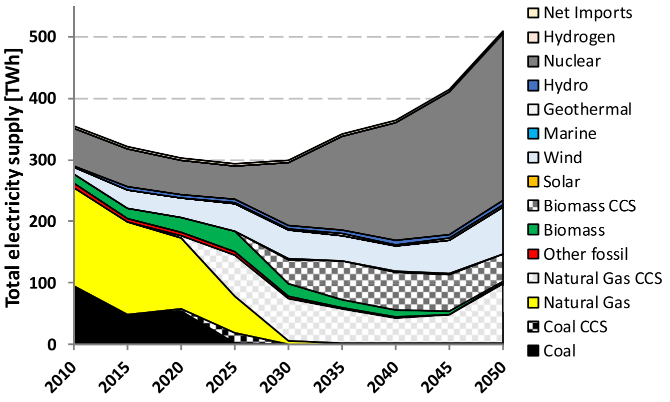

Fig. 3. Development of electricity supply by fuel type in the UK in the reference case.

In terms of electricity demand, the initial reduction until 2030 can be explained by a rising use of efficient appliances in the buildings sector (most importantly for lighting) and an absolute decline in the electricity use in the industry sector mostly in line with the falling production levels in energy-intensive branches. Afterwards, an increased trend to electrification can be observed mostly due to a strong expansion of heat pumps in residential heating and a rising contribution of electric cars to road transport demand.

It has to be noted that these results are driven by the highly uncertain cost trajectories assumed in UKTM. In particular, significant uncertainties exist around the future of nuclear energy in the UK and the commercial availability of CCS technologies. As a less optimistic trajectory for either of the two would correspondingly enhance the prospects of the other, competing technologies, we will further explore different cases of technology failure in the sensitivity analysis (see also [24] for an extended analysis of technology failures).

To highlight the current situation of marine energy in the UK system, Fig. 4 presents the levelized cost of electricity (LCOE) for key generation technologies in the reference case. The rising carbon price leads to increases in the LCOE of fossil fuel technologies, even with CCS. Accordingly, a huge drop in costs occurs for bio CCS plants until 2035. Afterwards, the growing competition puts pressure on prices for bioenergy resources such that the LCOE for bioenergy technologies rise again significantly. Both for onshore and offshore wind farms, relatively moderate learning effects are expected such that the LCOE reach 84 £/MWh and 101 £/MWh by 2050. Based on the DDM cost assumptions, nuclear power plants exhibit with 65 £/MWh the lowest generation costs in 2050.

This emphasizes the challenge that marine technologies currently face in the UK energy system. With capital costs of 6000 £/kW, operating and maintenance cost at 3% of capital costs and a capacity factor of 31%, the marine technology modelled in UKTM starts with LCOE of 326 £/MW. Thus, to reach competitiveness with other generation types, this cost would have to decrease to less

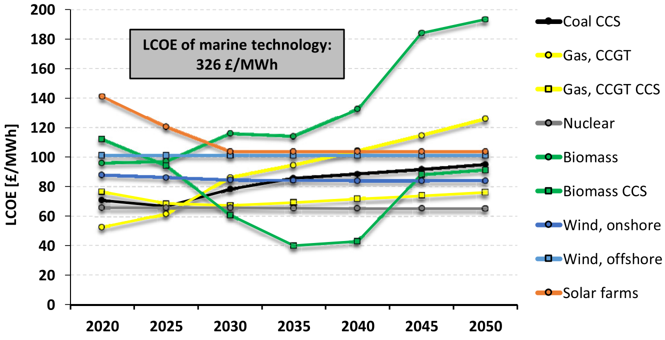

Fig. 4. Development of LCOE of key technologies in the reference case.

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[2] The actual cost figures of the DDM version underlying UKTM have not been published. However, the resulting levelized costs of electricity are presented in Fig. 4.

Table 2
Marine capacity installed in 2050 across the scenario matrix (with GD = global deployment, LR = learning rate, TF = technology failure, SO = learning spill-overs from offshore wind).

	GD	LOW				HIGH			
SO	TF \ LR	5%	10%	15%	20%	5%	10%	15%	20%
NO	-	0.0	0.0	0.3	13.9	0.0	0.0	13.9	24.5
	No CCS	0.0	5.2	13.2	18.1	0.0	9.1	14.3	24.5
	Low NUC	0.0	0.0	1.7	14.3	0.0	0.0	13.9	24.5
	Low RE	0.0	0.0	0.3	13.9	0.0	0.0	13.9	24.5
	Combined	14.3	24.5	24.5	24.5	14.3	24.5	24.5	24.5
YES	-	0.0	0.0	0.9	13.9	0.0	0.0	13.9	24.5
	No CCS	0.0	5.4	13.9	23.9	0.0	10.7	14.3	24.5
	Low NUC	0.0	0.0	5.2	14.3	0.0	0.0	13.9	24.5
	Low RE	0.0	0.0	0.9	13.9	0.0	0.0	13.9	24.5
	Combined	14.3	24.5	24.5	24.5	15.7	24.5	24.5	24.5

🟩 > 20 GW
🟩 10-20 GW
🟨 5-10 GW
⬜ 0-5 GW
🟥 0 GW

than 100 £/MWh before 2050, i.e. would have to fall to less than a third of today's cost. Under which conditions that could be the case or which other factors might influence the role of marine technologies in the UK electricity system is explored through a sensitivity analysis in the next section.

3.2. Sensitivity analysis — impacts on the electricity system

The sensitivity analysis explores the impact of four key parameters on the diffusion of marine technologies in the UK energy system: the learning rate (LR), global deployment (GD), failure in other key generation technologies (TF) and possible learning spill-overs from offshore wind capacity (SO). As a first step, the installed marine capacity in 2050 across the 80 sensitivity runs is compared (Table 2). In 2030, 4 GW of the marine technology are installed in all scenarios as a result of the assumed strategic development of the national market. Afterwards, however, the optimisation approach of UKTM decides whether further marine capacity is installed.

The results of the sensitivity analysis in Table 2 show that the assumed learning rate and the assumptions on technology failure have the strongest impact on the long-term diffusion of marine technologies. Learning rates of 5 or 10% are generally too low to incentivise further investments such that the marine capacity, assumed to have a lifetime of 20 years in the model, is even phased out by 2050. With learning rates of 15% or 20%, the deployment in the UK depends strongly on the global capacity which defines the learning effects. A full exploitation of the assumed available marine potential of 25 GW by 2050 only occurs with a learning rate of 20% and the high global deployment trajectory (notwithstanding the cases with multiple technology failure). Also, at a 15% learning rate and without key technology failures, significant investments (>10 GW) are only realized in combination with high global capacity, while with low global deployment a learning rate of 20% is needed to induce similar investment figures. Looking at the cases with failure in other key generation technologies shows that restricting the capacity of nuclear power or of other renewable generation technologies generally has no impact on the diffusion of marine technologies, as there are still cheaper options that could replace the missing capacity. In contrast, the contribution of marine energy is higher under the assumption that CCS does not become commercially available with significant investments already at a learning rate of 10% and high global deployment. This highlights the importance of bio-CCS as a safety valve for the energy system. If bio-CCS is not available, the electricity system is still fully decarbonized, but as there is no longer the option to produce negative emissions, a stronger electrification of the end-use sectors also takes place as their contribution to emission mitigation needs to rise.

The case of a combined failure in nuclear, renewable and CCS technologies puts extreme pressure on the decarbonisation of the electricity system such that a strong contribution of marine technologies is required even at a low learning rate of 5%. Comparing the scenarios with and without learning spill-overs from the national offshore wind capacity does not reveal any substantial differences indicating that the here assumed spill-over effects are not significant enough to influence the competitiveness of marine technologies.

Thus, the sensitivity analysis has shown that a significant contribution of marine energy to the UK energy system only occurs in an environment of significant learning (with rates of 15% or

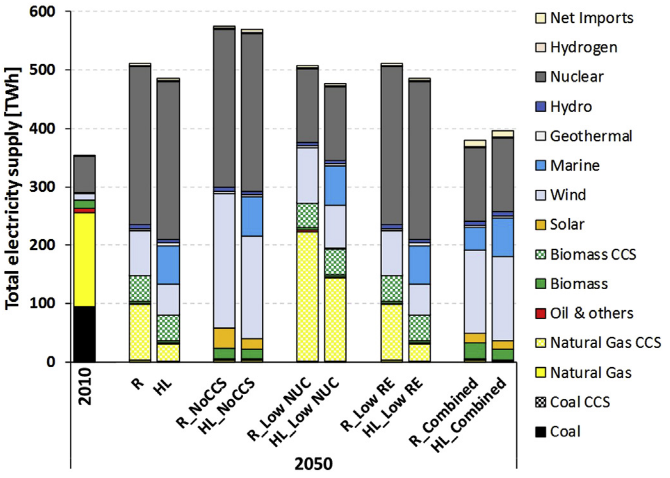


Fig. 5. Comparison of electricity generation in 2050 in scenarios with high marine learning (HL) and the respective reference scenarios (R, without marine learning) for different cases of technology failure.

above), high global deployment or multiple failures in other low-carbon generation options. Not all technology failures are equal, however: Failure of CCS technology alone is able to induce marine investments throughout to 2050, except if the learning rate is very low. In light of the still uncertain future of CCS [89], marine could possibly provide a hedging strategy against CCS failure (although as we'll soon show, also for CCS failure a learning rate of at least 15% is required before the early investments can be justified in terms of costs).

To further explore what an energy system with high penetration of marine energy would look like and what technologies it would replace, the electricity generation mix for 2050 is presented in Fig. 5 comparing high marine scenarios (20% learning rate and high global deployment) with the respective reference scenarios (no learning in marine technologies) for different cases of technology failure.

In general, marine technologies replace the next most expensive technology according to the merit-order curve. In the case with no assumed technology failure, this is the majority of offshore wind generation and part of the natural gas CCS plants. Hence, the renewable share in electricity generation in 2050 increases to 36% in the high marine scenario compared to 26% in the respective reference and the electricity sector contributes with an additional 6 Mt CO_2eq to emission mitigation. Accordingly, the pressure on the end-use sectors to reduce emissions is diminished, resulting in a slightly lower electrification of demand. Similar trends can be observed in the scenarios with limited availability of nuclear power or renewable generation options. By contrast, in the cases without CCS, marine energy replaces intermittent renewable generation, both from offshore wind and solar photovoltaics. Also, total electricity demand is about 15% higher than in the cases without technology failure, as here, without the option to generate negative emissions through bio-CCS, the end-use sectors have to contribute more strongly to emission abatement through electrification. In the highly constrained scenario with the combination of technology failures, electricity generation is reduced by roughly a quarter in 2050 compared to the case without technology failure and marine energy is even deployed in the absence of learning effects. With high learning rates, the marine contribution is almost doubled and used mainly to increase electricity generation.

Hence, the analysis of the scenarios with the most favourable conditions for marine energy shows that in 2050 the contribution of marine technologies could reach the full potential assumed in this scenario analysis for the UK of about 66 TWh covering between 12 and 17% of total electricity generation in the UK.

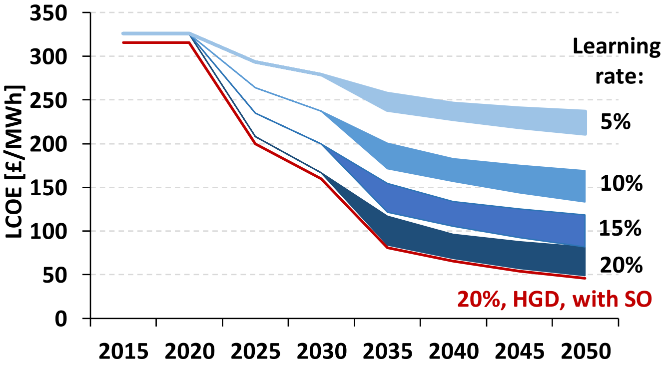


Fig. 6. Development of LCOE for marine energy in the sensitivity analysis (coloured areas show difference in LCOE with the same learning rate but with low or high global deployment (HGD), values shown are without learning spill-overs from offshore wind (SO) except of the red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.3. Cost

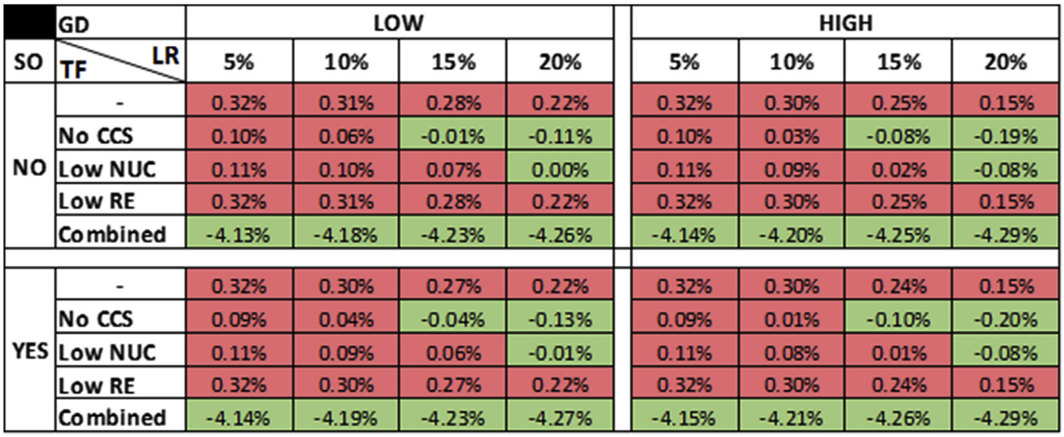
The analysis with UKTM has shown that, with strategic development of a national lead market until 2030, marine energy could achieve a significant share in the UK electricity system by 2050, if high learning rates and strong global deployment prevails. In this section we will analyse what this would mean in terms of costs for the energy system. Fig. 6 summarises the LCOE trajectories across the range of learning rates and levels of global deployment.

Starting from 326 £/MWh in 2020, considerable cost reductions are already realized during the establishment of the national market where learning effects are assumed to depend on the nationally installed capacity alone. In 2030, the LCOE range between 160 and 280 £/MWh. After that, the LCOE vary strongly according to the imposed learning rate and global deployment trajectory resulting in a considerable range from 50 to almost 240 £/MWh in 2050. As suggested by the comparison of future generation costs of key technologies (see Fig. 4), significant deployment of marine energy only takes place if the LCOE falls below 100 £/MWh. The threshold level is higher, if other low-carbon generation options fail, as for example, without CCS, LCOE of 170 £/MWh are sufficient to induce some marine investments by 2050. In terms of capital costs, LCOE of 50 £/MWh would correspond to around 900 £/kW, well below the current level for onshore wind farms. As already indicated by the results of the sensitivity analysis in Table 2, the possibility of positive spill-over effects in learning from national offshore wind capacity has only a marginal effect on the LCOE of marine energy (shown in Fig. 6 by the difference between the red line (LCOE with learning spill-overs) and the lower end of the dark blue area (LCOE with the same learning rate and global deployment but without learning spill-overs)). Also, and as could be seen in Table 2, it's clear that for LCOE the learning rate plays a much bigger role than global deployment – having a higher learning rate, but lower global deployment (nearly) always leads to a lower LCOE value than a lower learning rate and higher global deployment does.

In the next step, we assess whether the strategic investments into a national lead market for marine energy technologies pays off in the long-term by reaping the benefits from global learning effects. The assumption is that in absence of UK's early efforts, global learning never takes off and we will follow the reference scenario. Conversely, any UK benefits that are gained from the post-2030 cost reductions in the learning scenarios are assumed to be direct consequences of early UK action. Focusing on the energy system-wide cost implications, we compare the cumulated discounted welfare costs for the entire model horizon between the sensitivities with learning and the respective reference cases without marine learning but the same technology assumptions otherwise. Total societal welfare costs are defined as the net total surplus of producers and consumers and comprise the entire costs of a specific energy system, covering capital costs for energy conversion and transport technologies, fixed operating and maintenance costs as well as fuel and certificate costs. It has to be noted that this assessment covers the entire energy system, but does not include wider macro-economic effects, like impacts on employment or GDP.

The numbers in Table 3 show that in most cases, the early strategic investments into marine energy lead to a rise in societal welfare costs compared to the respective cases without a marine push and the learning that follows. The cost increase is, however, small with a maximum of 0.32% or £35 billion cumulated over the entire model horizon. Yet, some exceptions need to be pointed out for cases with considerable technology failure showing that developing a market for marine technologies could be seen as a hedging strategy against uncertainty in other low-carbon

Table 3
Change in discounted welfare cost in the sensitivity runs compared to the respective reference (without learning and strategic marine investments) (with GD = global deployment, LR = learning rate, TF = technology failure, SO = learning spill-overs from offshore wind).



	GD	LOW				HIGH			
SO	TF LR	5%	10%	15%	20%	5%	10%	15%	20%
NO	-	0.32%	0.31%	0.28%	0.22%	0.32%	0.30%	0.25%	0.15%
	No CCS	0.10%	0.06%	-0.01%	-0.11%	0.10%	0.03%	-0.08%	-0.19%
	Low NUC	0.11%	0.10%	0.07%	0.00%	0.11%	0.09%	0.02%	-0.08%
	Low RE	0.32%	0.31%	0.28%	0.22%	0.32%	0.30%	0.25%	0.15%
	Combined	-4.13%	-4.18%	-4.23%	-4.26%	-4.14%	-4.20%	-4.25%	-4.29%
YES	-	0.32%	0.30%	0.27%	0.22%	0.32%	0.30%	0.24%	0.15%
	No CCS	0.09%	0.04%	-0.04%	-0.13%	0.09%	0.01%	-0.10%	-0.20%
	Low NUC	0.11%	0.09%	0.06%	-0.01%	0.11%	0.08%	0.01%	-0.08%
	Low RE	0.32%	0.30%	0.27%	0.22%	0.32%	0.30%	0.24%	0.15%
	Combined	-4.14%	-4.19%	-4.23%	-4.27%	-4.15%	-4.21%	-4.26%	-4.29%

generation options. The achieved cost reductions are still comparatively insignificant in scenarios with restricted availability of nuclear power or CCS and only occur in combination with high learning rates for marine technologies. By contrast, cumulated welfare costs are lowered by up to 4.3% (around £550 billion) in the scenarios with combined failure in CCS, nuclear power and renewable electricity options. It's worthwhile noting that although 10% learning rate is enough to induce post-2030 investments in marine technology with CCS failure (see Table 2), the benefits gained during the post-2030 period are not enough to balance the extra costs suffered during the national rollout of the technology.

This remarkable cost difference, which occurs even in the cases with relatively small learning effects, can be further explained by looking at the carbon prices across the scenario matrix. In the cases with full technology availability, the marginal GHG abatement costs rise from 30 £/t CO_2eq in 2020 to 390 £/t CO_2eq in 2050. Generally, carbon prices are relatively stable across the sensitivities in the learning rate, global deployment and spill-over effects. On the contrary, the assumptions on technology failure lead to a rise in the carbon price to up to 810 £/t CO_2eq in 2050 (combined case). Here, the availability of less costly marine energy can significantly alleviate the cost burden by allowing an increase in electricity generation and a lower uptake of costly mitigation options in the end-use sectors leading to a reduction in the carbon price to 660 £/t CO_2eq in 2050 in the scenarios with combined technology failure and high learning.

3.4. Benefits to the electricity system

Other possible benefits from supporting the deployment of tidal energy, and not fully captured by our UKTM modelling, include the creation of jobs, new export opportunities, increased regional development and providing a stable, renewable electricity supply throughout every hour of the year. As an example, we take the latter of these possible benefits and assess it further using highRES [84,85], a model with higher temporal and spatial resolution than UKTM (more information on the highRES model and methodology of linking UKTM with highRES can be found in the Supplementary Material). Like other energy system models UKTM's coarse temporal and spatial resolution does not fully capture variable renewable energy (VRE) intermittency [76]. As a result it may undervalue the stable and predictable production tidal can provide. Note that we only study tidal energy as wave energy production correlates with wind energy [53] and therefore provides no similar balancing benefits as tidal.

Due to the spatial and temporal variability of VREs, high penetration levels could lead to increasingly large disparities between hourly electricity supply and demand adding system integration costs. Possible advantages from adding tidal energy to the system include technological diversification, a predictable[3] form of renewable supply and spatial diversification of production which could lead to the supply of renewable firm power and match a substantial portion of base load [12,61].[4]

Of all the UKTM scenarios, the "No CCS scenario" results in the highest share of VREs in 2050 and is therefore the most appropriate scenario for studying the system integration benefits that may be gained from adding tidal energy to the system. UKTM represents the entire energy system and thus has the advantage of being able to assess which sectors get electrified and what is the resulting total electricity demand. We use this electricity demand and the portfolio of non variable renewable energy technology capacities taken from the UKTM results of the "No CCS scenario" for 2050 and use them as inputs in the highRES model (see Table 4). We run two different scenarios:

1. The "REF highRES scenario" for which we use the capacities of the UKTM "No CCS reference scenario" (i.e. the scenario that assumes no marine push). For the purpose of this section of the paper we use the name "UKTM REF" for the results of the UKTM "No CCS reference scenario".
2. The "tidal highRES scenario" for which we use the UKTM scenario "No CCS, 20% learning rate, high global deployment, no technological spillovers". As above we use the name "UKTM tidal" for the results of the "No CCS, 20% learning rate, high global deployment, no technological spillovers scenario".

As for UKTM, we assume that the maximum capacity of tidal energy available for highRES amounts to 24.5 GW. In other words, highRES is free to invest in as much tidal as it wants up to 24.5 GW.

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[3] Tidal energy is produced from the rotation of the earth relative to the sun and the moon, resulting in two high water and low water events per day [66,90,91].Spring tides occur when the moon and sun are in line with each other which causes the tides to be reinforced. At half-moon weaker tides called neap tides take place [53].

[4] With the exception of spring and neap tides.

Table 4
Non VRE capacities and demands taken from UKTM (2050) and used as input in highRES.

UKTM input	REF highRES scenario	Tidal highRES Scenario
Nuclear capacity (GW)	34.2	34.2
Biomass capacity (GW)	6.8	5.7
Hydropower capacity (GW)	1.64	1.64
Geothermal capacity (GW)	0.5	0.5
Interconnection capacity (GW)	5.8	5.8
Electricity demand (TWh)	570.82	560.42

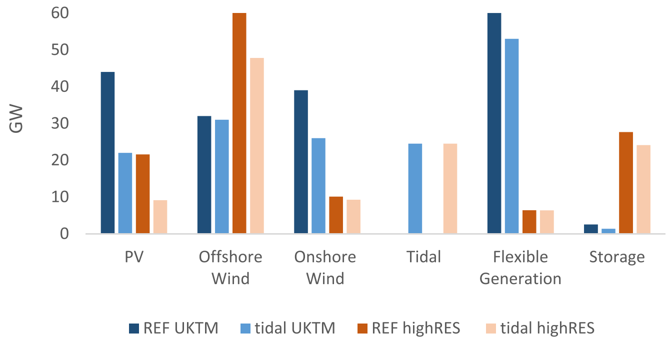

Fig. 7. Installed capacities of VREs, flexible generation and storage in the UKTM and highRES references.

We use the same technology investment costs in highRES as in UKTM (i.e. the costs for tidal energy in the "tidal highRES scenario" include learning).

For both scenarios highRES decides on the cost-optimal dispatch, VRE generation (including tidal) investments and VRE integration options investments as well as on the location of all generation technologies and integration options. VRE integration options considered are transmission grid extension, electricity storage and flexible gas turbines. We therefore allow highRES to not only assess balancing benefits of marine for the portfolio defined by UKTM, but allow highRES the possibility to suggest a different VRE portfolio, based on the more detailed spatial and temporal modelling. We then compare the scenarios and assess how tidal energy affects the composition of the VRE electricity system.

Fig. 7 shows that in UKTM tidal energy replaces part of PV (−50%, when compared to the REF scenario), onshore wind (−33%) and offshore wind (−5%) capacities, with matching reductions in production. Following the pattern observed in UKTM, highRES replaces PV (−58%), offshore wind (−21%) and onshore wind (−8%) capacities which are all more intermittent than tidal energy. In terms of VRE integration options, in the UKTM tidal compared to the UKTM REF scenario the model installs 12% less gas capacity and 48% less storage.[5] HighRES doesn't change the flexible generation capacity across the two scenarios, but installs 13% less storage and 18% less transmission grid extension (due to tidal being placed closer to demand centres than wind it replaced were) with the tidal in the system. In highRES, storage is used the same amount in both scenarios whereas it generates 27% less from flexible generation, even when the flexible generation capacity is kept unchanged. Further, highRES also imports 17% less through interconnection and produces 21% less from biomass energy (with a capacity reduction of only about 6%). For comparison, for generation sources with fuel costs, UKTM generates 10% less electricity from flexible generation, 5% less from biomass and imports the same amount of electricity.

Fig. 8 shows the location of VRE and tidal capacities as optimised by highRES. We see that tidal energy is being placed in the North of Wales and the South- East, taking advantage of the spatial diversification and resulting difference in timing of high and low tide. As UKTM does not have spatial detail, it isn't able to consider such diversification in its optimisation.

We find that the general patterns of electricity system design in UKTM are similar to highRES when tidal energy is introduced to the system. When looking at the individual technologies, however, UKTM, contrary to highRES, installs more onshore than offshore wind, but then in the tidal scenario, again contrary to highRES, reduces onshore production much more, even below offshore levels. HighRES, unlike UKTM, is able to optimise the placement of offshore wind around the UK, taking advantage of good capacity factors and different timings of production. Onshore wind, in turn, is only placed in Scotland in highRES, as the capacity factors are highest there. In the highRES tidal scenario the model chooses to keep the good onshore locations, as onshore is generally cheaper than offshore, and reduces offshore wind energy, disproportionally around Scotland. These spatial diversification benefits cannot be captured with the spatially aggregated UKTM model.

In UKTM tidal energy leads to higher reductions in the integration capacities needed (flexible generation and storage), but lower reductions in generation from flexible generation and baseload than it does in highRES. UKTM does not have the temporal resolution to adequately represent the intermittency of variable renewable energy technologies. The variability is represented by a different availability per time slice,[6] making it comparable to dispatchable generation but with a poor capacity factor. Due to its hourly resolution highRES sees the intermittency more accurately than UKTM and as a result needs the flexible generation and storage for events when renewable energy supply is low and/or demand is high. These events occur less often in the scenario with tidal energy and tidal energy even replaces some of the baseload generation.

Overall, we can conclude that UKTM and highRES follow similar patterns with the introduction of tidal energy. However, due to the low temporal and spatial resolution of UKTM, it is unable to capture all the detailed dynamics of the different technologies. highRES is better suited to study the specific benefits to the power system from introducing a stable and predictable renewable energy source. The lower investments in electricity storage and reduced usage of flexible generation in highRES allows us to conclude that tidal energy brings benefits to a low carbon electricity system which may not be adequately captured by the UKTM modelling framework.

3.5. *Scope and limitations of the research*

We conclude our discussion of the results with a brief note on some of the key limitations of our research. Firstly, the main tool we use in our research, UKTM, is a cost-optimizing model with perfect foresight and thus produces normative, quantitative projections in absence of any uncertainty, market power or consumer heterogeneity. The results therefore need to be understood in this context and are further conditional to the numerous assumptions that need to be made when parametrising the model. Secondly, being a cost focused model, UKTM does not represent well factors other than

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[5] albeit UKTM installing very little storage compared to highRES: 2.54 vs 23 GW in the REF highRES scenario.

[6] The year is divided into 16 time slices (4 seasons and 4 intra-day time slices).

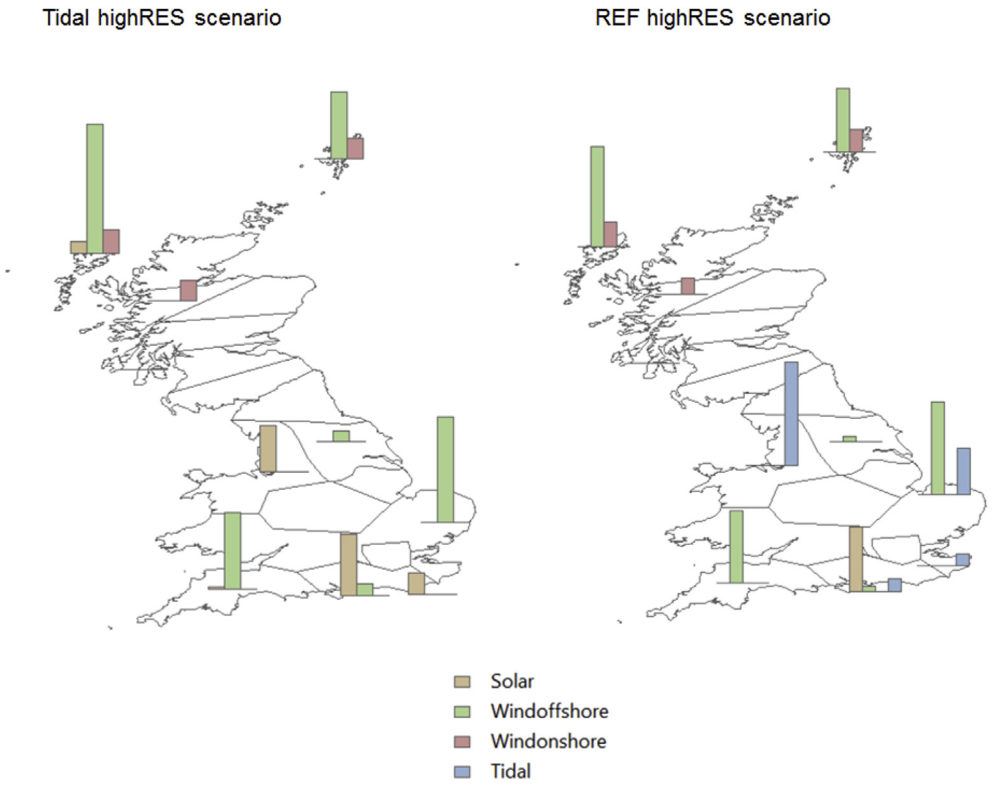

Fig. 8. Location of VRE and tidal capacities for the tidal highRES and REF highRES scenarios (exact capacities can be found in Table A1).

costs. Such factors, e.g. technology acceptance by the public, regional development concerns or other policy goals, can affect the deployment of technologies. Thirdly, the overall marine resource potential is uncertain, can change with future technological developments and, more generally, the study and most of its results and insights are specific to the UK. Fourthly, several simplifications are included in the modelling, e.g. we model tidal and wave energy as one technology, we focus on technology learning in terms of costs reductions from learning by doing, but do not consider R&D explicitly or include performance improvements for the learning (e.g. efficiency or lifetime improvements), modelling of technology spill-overs is limited to those from offshore wind to marine energy and UKTM, due to its lack of spatial detail, does not account for spatial cost differences related to e.g. grid connection (highRES takes into consideration transmission grid reinforcements, but not on an individual site basis).

4. Discussion and conclusions

The UK is currently in a favourable position to develop a national lead market for marine energy technologies having attractive natural conditions, experience in other maritime industries, substantial government support and high-quality research facilities. However, substantial learning effects would be necessary to bring marine technologies to maturity and even to a stage where they can compete with other low-carbon technologies.

Against this background, the present analysis has explored, from a systems perspective, whether strategic national investments into marine energy technologies in the medium-term and exploiting the global learning effects that are assumed to be induced by the early UK action in the long-term would benefit the UK energy system by contributing to the decarbonisation of the electricity system. The sensitivity analysis conducted here has allowed us to systematically assess the impact of key drivers of technology deployment.

Our analysis highlights the magnitude of the challenges for the marine energy industry and raises several issues regarding the benefits of establishing a lead market in the UK:

1) The results of the whole energy systems analysis indicate that very favourable conditions, i.e. high learning rates and global deployment, would be required to enable a substantial contribution of marine energy to the UK energy system in the long-term. Yet, it is highly uncertain that learning rates above 15% and a globally installed capacity of more than 150 GW by 2050 will indeed materialise.
2) Alternatively, marine energy technologies could be conceived as a hedging strategy to avoid prohibitive decarbonisation costs in the case of failure in other key low-carbon options. In light of the considerable uncertainties regarding the appropriate long-term decarbonisation pathway, promoting a diverse technology portfolio has often been highlighted as one of the key strategies [13,81]. Yet, given the fact that there are alternative technology options which are closer to cost-competitiveness, it might be more beneficial and less risky to concentrate policy support on these options, especially since significant cost benefits can only be gained in case of multiple technology failures. Developing marine technologies might also provide cost benefits in the case of CCS not being commercially available, which, given the current technology development, does not seem unlikely. The benefits in terms of system costs calculated in this analysis are, however, rather low – especially when compared to the additional costs that developing a marine market in the UK would induce if *no* technology failure (or even with a “renewable failure”) took place.

3) The issue of timing also plays against marine technology. Most scenario analysis indicates that emissions from the UK electricity system need to be reduced significantly by 2030 to stay on track with the 2050 target – to less than 100 g CO2/kWh [11,68]. Consequently, a massive roll-out of low-carbon generation will be required during the 2020s. It is therefore doubtful whether a technology which is here assumed to reach commercial availability on a global scale only after 2030 will be able to compete with the already established options.
4) The energy system-wide cost assessment indicates investing in a national marine market generally leads to a slight cost increase for the energy system (up to £35 billion), with the exemption of cases with multiple failure in other decarbonisation technologies. Here, it needs to be stressed that our analysis does not provide a comprehensive assessment of the economy-wide cost impacts in terms of GDP or job creation. These effects are very difficult to estimate, especially those related to export opportunities [3]. have found positive macroeconomic impacts for investments in marine capacity in Scotland based on CGE and input-output modelling exercises, while [44] estimate the possible contribution of a marine energy market to UK's GDP at £1.4–4.3 billion by 2050, based on a 15% share in the global market. Yet, one must not forget that equal or even higher benefits might be created through the promotion of other industries. One aspect that has to be highlighted particularly for the marine energy industry, is its potential to contribute to regional development of coastal areas that have long benefitted from the, now declining, offshore oil and gas industry [39].
5) Integrating low-carbon technologies into the existing generation system will be a major challenge given their often decentralized and intermittent nature [80]. That is why we have also examined whether a further justification for the deployment of marine technologies could be found in their (renewable) contribution to system balancing. Our analysis indicates that including marine technologies has benefits in terms of reduced VRE integration measures needed to balance the system, especially when the temporal and spatial detail of the assessment is increased.
6) Given that it is still in the early stages of development, and marine energy as such lags behind other low-carbon options, the UK government would have to be willing to provide sustained, ongoing support for the marine energy industry, at least until 2030. Apart from the need to drive down costs through continued research and demonstration projects, support is required for the development of national supply chains as well as for upscaling efforts to prove the commercial potential. Such long timeframes are challenging and recent experience, like the cancellation of the CCS Commercialisation Competition, providing £1 billion capital funding [30], puts this prospect in serious doubt.
7) Lastly, the long-term value for the UK system depends strongly on whether marine technologies will take off on a global scale as national learning effects are unlikely to be sufficient to establish cost-competitiveness. Both the International Energy Agency [32] and the International Renewable Energy Agency [34] highlight the significant potential of wave and tidal energy, but emphasize at the same time the substantial barriers that put the development at risk. Hence, in terms of long-term export opportunities and economic benefits, it might be less risky to concentrate on an already more mature industry where the UK also has the potential to become a market leader, like offshore wind energy or CCS.

Thus, on the whole, we conclude that marine energy has the potential to contribute to the UK energy system, but there is a substantial risk that the initial strategic investments in a national lead market will not directly pay off in the long term. Accordingly, while it may not be time to “pick winners” for the decarbonisation strategy out to 2050, it might be necessary to “accept losers” at some point, keeping in mind the value of diversity in the technology portfolio on the one hand and the cost of keeping the options open on the other hand. Furthermore, we would like to emphasize the need for long-term stable policy support, if the UK is to establish a central role in any low-carbon technology market. As one example for an additional benefit from the deployment of marine technologies we investigate if tidal energy can provide a stable, renewable electricity supply. Future research analysing additional benefits such as job creation, new export opportunities, increased regional development would provide an even more comprehensive view.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.renene.2017.07.092.

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