Export cable rating optimisation by wind power ramp and thermal risk estimation

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Abstract
This paper demonstrates the impact of using realistic wind power generation profiles, time-varying ocean bottom temperatures and hypothetical wind farm over-planting scenarios on export cable capacity optimisation. Given the inherent risk in over-planting, a novel hour ahead thermal risk estimation method was developed to foresee and mitigate cable temperature exceedance, employing a preventive curtailment. Two offshore wind farm locations L1 (North-west European Shelf) and L2 (Australian Shelf) have been chosen for testing but utilising real wind and ocean bottom temperature data. These simulated results demonstrate a 10% rating increment over the static rating in L1 resulted in a 13% increment in the amount of energy delivered over a year (MWh/year) without any risk or instances of thermal overheating. Similarly, a 9.8% rating increment in L2 resulted in a 13.6% increment in annual energy transmission (MWh/year). The financial increment for both over-planting scenarios was approximately £9 million/year for the studied cases.

1 | INTRODUCTION

The accelerated development in the offshore renewable energy has lead to increased competition in the sector and the need to optimise the transmission capacity in offshore installations in order to reduce the levelised cost of energy (LCOE) offshore. Wind farm export cables are often rated by considering IEC60287 standard [1] which are known to generate conservative rating limits [2] that assume a continuous load in the cables.

This paper approaches the optimisation of export cable utilisation by means of a novel thermal risk estimation (TRE) algorithm that identify wind power ramp events and estimate its thermal consequences in submarine power cables. The algorithm is tested under hypothetical wind farm over-planting (WFO) scenarios (where installed capacity is higher than the static cable rating) [3], considering realistic wind power generation profiles and time-varying ocean bottom temperatures.

The fluctuating power transmitted by wind farm export cables depends on variable wind speeds which create far from continuous load currents with only short periods of maximum output current. Thus, the use of static rating cable limits along the fluctuating output power present in offshore cables leads to much lower conductor temperature profiles than in conventional cable installations [4]. Given that the cost of submarine export cables represents a significant part of the CAPEX of a wind farm, the export cable capacity utilisation is an essential part of project cost optimisation [5].

1.1 | Dynamic and cyclic cable rating methodologies

The alternative to the static cable ratings is the well-know dynamic rating calculations, which, estimate the amount of power that can be accommodated in real-time given measured conditions around the cable [6, 7]. Several dynamic rating methodologies have been widely studied and validated in [8–10] for land cable installations proving to improve load capacity compared to static ratings [2]. Nonetheless, the application of the existing real-time rating algorithms in offshore export cables could not generate similar benefits because the load current in an offshore cable is not driven by demand but by variable wind power generation availability.

Cyclic ratings can approximate the power output of cable by a cyclically varying load [11]; however, the literature evidence a limited amount of research applied in submarine cables. Efforts have been made to consider more realistic duty cycles for wind farm circuits to improve the calculations of thermal ratings; for
example, the authors in [12] study how the fluctuating power generation is reflected in the thermal rating of the cable and a cyclic rating technique is developed to optimise the export cable size.

The electro-thermal studies in [13] and [14] look into the use of realistic load current profiles for offshore cable sizing with the objective of CAPEX optimisation. A submarine export cable connected to a wave farm was studied in [13] and the results demonstrate that due to the fluctuating current profiles generated a cable size 50% smaller could be used in the farm while keeping a safety margin of cable temperatures (below 90°C). Similarly, the results in [14] shown that using environmental data from the wave farm location along an increased wFO factor could allow a reduction between 10%-20% of the export cable size. Finally, in [15] the thermal behaviour of the aerial, buried and submarine sections of an export cable were analysed considering the variability of the load as well as the cooling effect of environmental parameters around the cable concluding the possibility of cable sizing optimisation due to lower realistic temperatures.

An example of an industrial application considering a realistic duty cycle was presented in [16] where a worst-case dynamic load profile is derived from historical data and used in the planning stage of the Horns Reef 3 400 MW offshore wind farm by the Danish TSO Energinet. The use of the proposed cable rating technique demonstrated the possibility of a 25% reduction in cable size for the studied case.

These studies evidenced the ability to reduce cable sizes in cable systems with highly variable loads considering a more realistic submarine cable scenario. Increments in wind farm cable ratings, above traditional static ratings, are feasible, however, a methodology to estimate hours ahead the cable thermal state is needed to avoid thermal damage and unnecessary power curtailment when WFO is applied.

1.2 Wind power ramp forecasting

Wind power variation of different magnitudes (ramp events) are the main drawback characteristic of wind energy sources; thus, their integration to the network has brought the necessity to develop new ways of predicting ramp events in order to manage supply and demand. The idea of ramp events forecasting has grown rapidly paying special emphasis on the basis that large and fast power variations are critical enough to be targeted separately rather than focusing on the full wind power forecasting profile (see [17]).

The definition of ramp event has not been strictly formulated until now however, is generally characterised by a magnitude, duration, ramp rate and direction (±). Similarly, the criteria for ramp identification and classification has not been generalised; thus, several approaches are proposed in the literature going from a binary classification (ramp/no ramp) to more sophisticated methods [17].

Additionally, due to the novelty of the topic, there is still no agreement on how to approach or evaluate the ramp identification problem, for instance, ramp event alarms, on-line ramp identification/detection, forecasting of ramp rates and probabilistic ramp event occurrence methods are seen in the literature [18].

The literature found related to wind power ramp event analysis is focused on the study of onshore wind power systems in order to help reliability issues in power grid operations, intelligent distribution, electric grid management and future smart grid market mechanisms. A ramp detection algorithm which analyses and extracts ramp parameters is seen in [19] where a classification framework with ramp rules and scoring functions identifies wind ramps from a large time series. The characterisation framework was well established, however, no attempt to forecast ramps or perform real-time recognition was made as done in [20] where an online recognition method is presented. The work in [20] establishes a ramp model where an event consists of several linear wind power variation segments from which the ramp rate and future power are derived from the detected amplitude and duration.

Machine learning algorithms such as neural networks [21] support vector machines [22] and hybrid SVM-Markov Chain enhanced model [23] have been used to forecast power ramps. These classification-based algorithms, analyse wind power data to predict the class or per unit value of power fluctuations in a window of between 1–24 h ahead.

Unlike the approach in [19] where long-duration ramps were avoided, the work in [24] targets the statistical characterisation of extreme ramp events which particularly affect operation planning in systems with high wind penetrations are proposed. The proposed methodology target the analysis of large reductions of power (ramp down) in a 10 min resolution based on extreme value theory aiming to help the system operators in planning and perform actions when large negative power fluctuations are foreseen.

Wind power ramp estimation, to the best of the author’s knowledge, was not found for the case of offshore wind farm cables. Overall, the power ramps algorithms in the literature seemed to be based on a classification approach which analyses large data sets to extract traits and parameters which can then be used to identify/estimate wind power fluctuations. In this paper a classification approach will be applied for the case of historical data corresponding to two offshore wind farm locations.

1.3 Paper contribution

In [25], the authors presented a probabilistic methodology for the hours ahead TRE in submarine power cables. The methodology used 5 years of historical data and Markov Theory to estimate the hours ahead load current and likely cable thermal risk. The simulated use of the TRE methodology along hypothetical wind farm over-planting increments and a power curtailment strategy generated additional power delivery between 7.26% and 9.67% per year compared to the annual power delivered (Wh/year) using traditional continuous rating limits [25].
and shown to generate additional financial thus reducing the LCOE of the wind farm studied [26].

Although the objective of [23] and the present work is the optimisation of wind farm cable utilisation, the methodologies are not to be confused. The novel TRE algorithm proposed in this paper is based solely on the study of historical power ramps to identify real-time ramp variations. Bayesian reasoning is used to estimate their thermal consequences in the cable and, evaluate the probability of thermal risk 6h ahead. Other key differences in this investigation are the inclusion of the thermally limiting section of the cable; the use of realistic environmental data, that is, variable sea bottom temperatures and the use of two geographical locations to demonstrate the methodology adaptability.

The utilisation of the novel algorithm along with realistic environmental data from the wind farm locations, and WFCO could help to capture more power when wind speed is low while output power is curtailed when long periods of maximum power output are present in the cable. The proposed methodology would allow the monitoring of future temperature in the cable system to guard against thermal damage in the cable while allowing the cable utilisation to be optimised thus generating additional financial benefits and the LCOE reduction.

The use of realistic environmental data is essential for a realistic thermal risk estimation as shown by recent studies that show the complex role of environmental parameters in the heat dissipation process in cables buried under the seabed. For instance, the thermal properties of sediments are known to vary throughout the cable length, both due to natural variability and the installation process, while burial depth can vary due to post-installation seabed movement [27] [28]. Despite advances in the knowledge of heat dissipation process in submarine cables, it is unsure how these and other environmental variables, such as space and time-varying ambient temperatures around the cable, will impact future export cable rating calculations. Nevertheless, the use of more realistic wind power generation profiles and time-varying ocean bottom temperatures on export cable capacity optimisation has already been shown beneficial in [13] and [14].

The cable system studied in this paper include both the submarine and landfall sections. These are monitored using a real-time finite difference cable model (FDM subst) while a parallel algorithm performs a 6 h ahead estimation of cable temperature (FDM sub). The risk of thermal overheating is estimated and managed through online preventive curtailment. The methodology is evaluated considering WFO scenarios and the presented simulated results were obtained from two hypothetical offshore wind-farms in the NW European shelf and the Bass Strait (Australasia). The actual locations nominally correspond to the Dogger Bank wind-farm licence area (L1), while the Bass Strait corresponds to the region of the Star of the South Wind Farm licence area (L2). These locations are chosen to demonstrate the implications of significantly contrasting wind and ocean regimes on offshore wind farm rating and assets optimisation.

The studied submarine cable system comprise a 132 kV 3-core XLPE insulated cable, 800 mm² copper conductor for the thermal section in the sea (S1) and a 132 kV 3-core XLPE insulated cable, 1400 mm² copper conductor for the landfall thermal section (S2), which is know to be a thermally limiting spot along the line, see Figure 1. The maximum temperature limit of both cable sections is $T_{lim}=90^\circ$C. The calculated static rating of the cable sections is calculated as per IEC60287[1] considering fixed parameters around the cable. For instance, S1 consists of 1000 mm burial depth and 0.7 KmW$^{-1}$ soil thermal resistivity while the S2 consider a 4000 mm burial depth and 1.0 KmW$^{-1}$ soil thermal resistivity. The fixed water temperature is set according to the maximum water temperature reported in the corresponding location, for instance, 16.3°C in L1 and 19.8°C in L2 (See, section 2.3. for full discussion).

The calculated continuous ratings of the export cable sections are $I_{S1,au}=915 \, A$ and $I_{S2,au}=817 \, A$ for L1 and $I_{S1,au}=893 \, A$ $I_{S2,au}=797 \, A$ for L2. The calculated static rating of the cable sections in L2 is naturally lower than in L1 as the maximum temperature registered in the historical water temperature data are higher. Thus, warmer temperatures in L2 will force the cable rating to be reduced as per IEC60287[1] in order to avoid exceeding the cable maximum operating temperature.

### 2.2 Hypothetical wind farm sizes

The BWF examples are sized according to the thermally limiting section (S2) and the use of an 8MW wind turbine power curve. The BWF cases for each location are set as the maximum number of turbines connected without exceeding $I_{S2,au}$ in the case of L1 and $I_{S2,au}$ in the case of L2.

For instance, BWF in L1 is set as 23 wind turbines with a maximum output current of $I_{S2,au}=805 \, A$, while the BWF in L2 is set as 22 wind turbines with an $I_{S2,au}=770 \, A$. Seven hypothetical WFO cases are simulated for each offshore location represented by the addition of wind turbines which will increase the wind farm output $I_{max}$ as per Table 1 for L1 and Table 2 for L2.
TABLE 1 Hypothetical WFO for the North Sea case study

| Overplanting Case | No. of WT | $I_{max}$ | Increment over $I_{32_{	ext{dur}}}$ | Increment over $I_{16_{	ext{dur}}}$ |
|-------------------|-----------|------------|----------------------------------|----------------------------------|
| BWF               | 23        | 805 A      | -                                | -                                |
| WFO 1             | 24        | 840 A      | 2%                               | -                                |
| WFO 2             | 25        | 875 A      | 6%                               | -                                |
| WFO 3             | 26        | 910 A      | 10%                              | -                                |
| WFO 4             | 27        | 945 A      | 14%                              | 2%                               |
| WFO 5             | 28        | 980 A      | 19%                              | 6%                               |
| WFO 6             | 29        | 1015 A     | 23%                              | 10%                              |
| WFO 7             | 30        | 1050 A     | 27%                              | 13%                              |

TABLE 2 Hypothetical WFO for the Bass Strait case study

| Overplanting Case | No. of WT | $I_{max}$ | Increment over $I_{32_{	ext{dur}}}$ | Increment over $I_{16_{	ext{dur}}}$ |
|-------------------|-----------|------------|----------------------------------|----------------------------------|
| BWF               | 22        | 770 A      | -                                | -                                |
| WFO 1             | 23        | 805 A      | 1%                               | -                                |
| WFO 2             | 24        | 840 A      | 5.4%                             | -                                |
| WFO 3             | 25        | 875 A      | 9.8%                             | -                                |
| WFO 4             | 26        | 910 A      | 14.2%                            | 2%                               |
| WFO 5             | 27        | 945 A      | 18.5%                            | 5.8%                             |
| WFO 6             | 28        | 980 A      | 22.9%                            | 9.7%                             |
| WFO 7             | 29        | 1015 A     | 27.3%                            | 13.6%                            |

2.3 Historical wind and water temperature data

Two sets of actual, publicly available, time-varying wind speed and modelled annual ocean bottom temperature data are used in this paper.

The wind speed data for L1 was obtained through MERRA analysis [29] which is a NASA re-analysis program that generated global atmospheric datasets from 1979 to February 2016 [30]. On the other hand, the wind speed data for L2 was obtained from the Hogan Island Meteorology station in the northern Bass Strait (courtesy of the Australian Bureau of Meteorology). It is worth mentioning these wind farm projects are unrelated and they were geographically selected to demonstrate that the methodology can be applied in regardless of the differences in the input data.

The wind speed data for L1 is dated from 01/01/1979 to 29/02/2016 and is hourly sampled while the wind data from L2 is dated from 23/6/2010 to 24/10/2019 sampled every 10 min (re-sampled to hourly data steps for consistency). Previous work of the authors in [31] studied longer TRE estimation windows (12 and 24 h) for the case of wind farm submarine export cables which led to the selection of the 6 h window, as this time is enough for planning and performing curtailment in an offshore installations.

The data is divided into training and testing: 5 years of data are used in the ramp identification algorithm and 1 year is used for testing the thermal risk estimation methodology. The length of the training set was chosen to be 5 years, considering that this can be collected in early stages of offshore wind projects; for instance, TS1 corresponding to L1 is given by data from 01/01/2010 to 31/12/2014 while TS2 corresponding to L2 is given by data from 01/01/2013 to 31/12/2017.

For the NW European shelf the ocean bottom temperatures were extracted from the generated monthly average of the NW Shelf re-analysis of a hind-cast model run between 1992 and 2017 [32]. For the Bass Straits, the data was extracted from the mean monthly averages for 2016 from the shelf scale ocean model ozROMS [33].

Figure 2 presents the ocean bottom water temperature profiles for the given locations along with the typically used fixed profiles which correspond to the maximum temperature for each corresponding location (L1=16.3°C; L2=19.8°C).

Figure 3 (top) presents a box-plot corresponding to wind speeds extracted from the testing data in locations L1 per month. The bottom part of the figure presents the load current generation considering the BWF in L1.

The box edges indicate the 25th and 75th percentiles, the central red line indicates the median wind speed value for the month, the bottom and top whiskers extend to the most extreme duration times not considering outliers, which, are represented by the (*) symbol. The outliers are defined as the values that are more than three times away from the MAD. Let A denote the studied variable thus, $\text{MAD} = \text{median}(|A_i - \text{median}(A)|)$ where $i = 1, 2, 3 \ldots N$ is the number of observations.

Similarly, Figure 4 (top) presents the box-plot analysis corresponding to wind speeds extracted from the testing data in locations L2 while the bottom part of the figure presents the load current generation considering the BWF for the same location.

Evidently, there is a difference between the average wind speed patterns though out the year for both locations which are also evidenced in the output load current generation though out the year. For example, in L1 (Figure 3), there is a clear change in wind speeds during the warmer months of the year being the minimum and maximum mean average between 7.12 (ms$^{-1}$) and 12.45 (ms$^{-1}$). On the other hand, in L2 (Figure 4), the wind speeds throughout the year present a more constant pattern of wind speeds along the year being the minimum and maximum mean average between 8.67 (ms$^{-1}$) and 10.71 (ms$^{-1}$). Nevertheless, the mean annual wind speed for both locations is similar, being 9.8 (ms$^{-1}$) in the case of L1 and, 10.0 (ms$^{-1}$) for L2.

3 METHODOLOGY

The novel TRE algorithm starts with the analysis and classification of historical load current ramp events, which is performed only once, given the case study: cable size, WFO case and historical dataset. The general ramp characteristics are magnitude, duration, ramp rate, direction and the selection of a
certain threshold value \( t_h \). A ramp event in this paper is identified as the consecutive increments \( \pm \Delta I \) below a load current threshold defined as 85% output power which draws the boundary between a high to full load current (over \( t_h \)) and the ramp event zone (below \( t_h \)).

### 3.1 Historical ramp event analysis and forward thermal estimation

Let the load current generation at time \( t \) and \( t + \Delta t \) be \( I(t) \) and \( I(t + \Delta t) \), respectively. The time interval \( \Delta t \) here is 1 h given by the sampling step in the wind speed datasets TS1 and TS2. The analysis of the historical data starts by computing the difference between the consecutive values of load current data given by

\[
\Delta I = I(t + \Delta t) - I(t),
\]

where the sign of \( \Delta I \) indicates the direction of the increment (positive/negative). The ramp duration \( \Delta k \) and magnitude \( (I(t + \Delta k) - I(t)) \) is obtained from the dataset and stored for further analysis. The magnitude of the ramp event is given by \( I(t) \), which represents the load current at the identified
beginning of the ramp and $I(t + \Delta k)$ which is the load current at the end of the ramp.

The historical ramp events are studied on a monthly basis to calculate the ramp rate $R_{rate}$ of the individual ramps as

$$R_{rate} = \frac{I(t + \Delta k) - I(t)}{\Delta k},$$

where the resulting $R_{rate}$, $Ab^{-1}$ (Amps per hour) represents the average hourly rate of change ($\pm$) of load current. The obtained $R_{rate}$ values are classified according to the initial ramp intensity $\Delta L$ at the moment ($t$) of its identification.

The database built out of this study links the initial ramp intensity $\Delta L$ of each ramp event to its average hourly $R_{rate}$, which on a monthly basis captures the similarities in ramp intensity and duration.

The ramp event analysis described above is performed only once before the TRE methodology, while the methodology steps, explained in the following section, are performed at every time step (defined as 1 h).

### 3.2 TRE methodology overview

The calculation of conductor temperature is given by a FDM of the cable based on the cable thermal network of a submarine power cable introduced by Anders et al. in [34]. However, the proposed estimation procedure is independent of the cable model; thus, choosing a different cable model would not affect the steps in the TRE framework. Figure 5 presents the flowchart of the methodology steps which are explained in detailed below:

1. Considering actual load current $I(t)$ and the cable model, the FDM$_{main}$ routine calculates the actual conductor temperature $T(t)$.
2. If a $\Delta L$ below $th$ is identified, the direction and intensity of the ramp is compared against the historically built database to identify the likely $R_{rate}$ value and estimate the 6 h ahead consequences of the ramp event.
   For instance, if a load current increment/decrement below $th$ is detected, the intensity value $\Delta L$ is used to select the likely $R_{rate}$ value to approximate an expected load current $I_e(t + u)$ given by
   $I_e(t + u) = I(t) + (R_{rate} \times u)$,  
   (3)
   where $u$ is the estimation window ahead which is a fixed value selected as 6 h for the study cases.
3. The likely 6 h ahead load current ($I_e(t + u)$) is used as a first approximation rather than a point estimate value given the inherently stochastic nature of wind generation.
   Thus, a scenario sampling matrix $I_{sample}(t)$ is built by a MCS which generate likely series of load current scenarios considering the actual load current $I(t)$ in the vicinity of the expected load $I_e(t + u)$.
4. The FDM$_{sub}$ calculates the likely conductor temperatures $T'(t)$ considering the sampled future load current series $I_{sample}(t)$. The likely temperatures forecasted are used to create temperature pdf$T'(t)$.
   The steps 1 to 4 are run in parallel; thus, the conductor temperature $T(t)$ given by FDM$_{main}$ is used as the initial condition for the conductor temperature calculations $T'(t)$ in FDM$_{sub}$. The estimated conductor temperatures $T'(t)$
FIGURE 5 TRE methodology, flowchart

represent the likely cable temperatures in the following hours, thus:

5. A probability distribution function of likely conductor temperatures \( \text{pdf}_{T'}(t) \) for the future time window \( u \) is generated at every time step and used to calculate the likely thermal risk \( (\varepsilon_{\text{risk}}) \) that the cable could face in the following 6 h as

\[
\varepsilon_{\text{risk}} = \frac{T'(t+1, t+2... t+u) \geq T_{\text{limit}}}{u},
\]  

where \( T'(t+1, t+2... t+u) \) \( \in \) \( \text{pdf}_{T'}(t) \) represent the most likely series of load current values in the sampled distribution considering the median of the sampled \( \text{pdf}_{T'}(t) \).

6. The realistic risk \( r_{\text{risk}} \) is calculated considering load current testing data in order to evaluate the estimated risk. For instance \( r_{\text{risk}} \) is calculated as

\[
r_{\text{risk}} = \frac{T(t+1, t+2... t+u) \geq T_{\text{limit}}}{u},
\]

where \( T(t+1, t+2... t+u) \) are the conductor temperatures obtained by the FDM\( \text{main} \).

7. If a thermal risk \( \varepsilon_{\text{risk}} \) is estimated, a preventive curtailment reduce the load current input in the FDM\( \text{main} \) to the BWF rating, thus, \( I(t + 1) = I_{\text{BWF}} \) for 1 h. Note that, 1 h curtailment period is a conservative example that can be extended over longer times as required by the user/study case. This power reduction simulates the decision of the TSO to perform a reduction in power to avoid thermal damage to the cable.

During the next time step in the methodology, the updated (curtailed) and realistic (uncurtailed) \( I(t) \) becomes two parallel cable temperature profiles. An additional estimated thermal risk \( \varepsilon_{\text{risk}2} \) and new the realistic risk \( r_{\text{risk}2} \) are thus calculated in order to compare curtailed and uncurtailed profiles.

3.3 Methodology evaluation

The evaluation of the methodology is given by the comparison of the realistic risk \( r_{\text{risk}} \) (uncurtailed case) and the estimated
Economic benefits analysis

The online application of the methodology estimates and mitigates the risk of thermal overheating with the use of preventive power curtailment. The result is the maximising of the transmission capacity of the cable system while guarding against thermal damage in the cable. The additional power delivery from the application of the proposed methodology along the WFO cases is calculated for each case and used to estimate the LCOE of the wind farm export cable part.

The LCOE is an economic assessment of the total cost of a wind farm lifetime over the total energy output in the same period for the offshore location studied which for both locations did not exceed 75°C. Additionally, the temperature difference between the use of fixed versus variable water temperature parameters along the years proves to make a significant difference that can lead to the calculation of more accurate thermal ratings.

For this paper, the conventional static rating considering fixed water temperature is taken as the WFO scenario while the hypothetical WFO scenarios which represent less conservative approaches are calculated considering the variable water temperature profiles which for both locations did not exceed 75°C. Additionally, the temperature difference between the use of fixed versus variable water temperature parameters along the years proves to make a significant difference that can lead to the calculation of more accurate thermal ratings.

For this paper, the conventional static rating considering fixed water temperature is taken as the WFO scenario while the hypothetical WFO scenarios which represent less conservative approaches are calculated considering the variable water temperature profiles which for both locations did not exceed 75°C. Additionally, the temperature difference between the use of fixed versus variable water temperature parameters along the years proves to make a significant difference that can lead to the calculation of more accurate thermal ratings.

The economic benefit analysis presented in this section considers only the export cable capital price investment and power curtailment expenses to calculate the cable contribution to the LCOE per year as

\[
LCOE_{cable} = \frac{C_{\text{cable}} \times CRF}{E_{\text{WFO}}} + \frac{E_{\text{curtailed}}}{E_{\text{WFO}}},
\]

where \(C_{\text{cable}}\) (£) is assumed to be £1.2m per km which is a value consistent with information provided by [36] (considering only capital export cable figures); \(E_{\text{curtailed}}\) (E) is evaluated at an energy sale price of £72.50/MWh, the cable length is assumed as 50km.

The £72.50/MWh energy price used in the examples is a conservative value compared to the £39.65/MWh achieved during the CfD auction 2019 [37] for future wind farm projects.

Note that, the example values used in this paper such as energy price and cable capital cost does not undermine the results given by the TRE methodology but used to illustrate the possible financial benefit of its application.

4 | RESULTS

The results corresponding to the online thermal risk estimation and curtailment are performed over 1 year of testing, the year 2015 for L1 (UK) and the year 2018 for L2 (AU). The simulation generates 8760 estimations per data set and WFO case.

Firstly, the conductor temperature profiles for the year of testing is presented for L1 in Figure 6 and for L2 in Figure 7. Two thermal profiles are shown in each case corresponding to the fixed and variable bottom water temperature (left axis) while the difference between the two profiles is shown in the right axis.

The main characteristic in Figures 6 and 7 is the naturally low conductor temperatures due to the variable load current generation profiles which for both locations did not exceed 75°C. Additionally, the temperature difference between the use of fixed versus variable water temperature parameters along the years proves to make a significant difference that can lead to the calculation of more accurate thermal ratings.

For this paper, the conventional static rating considering fixed water temperature is taken as the WFO scenario while the hypothetical WFO scenarios which represent less conservative approaches are calculated considering the variable water temperature profiles corresponding to the offshore location studied. The amount of power delivered by the hypothetical BWF was calculated along the years of testing for each location and the results are presented in Table 4 along with the approximate annual revenue and LCOE\(_{cable}\) part calculated as explained in Section 3.3.1.

| Data set | BWF energy GWh/year | Approximate revenue £/year | LCOE\(_{cable}\) £/MWh |
|----------|----------------------|----------------------------|-------------------|
| L1 (UK)  | 962.96               | 69.81                      | 4.36              |
| L2 (AU)  | 921.2                | 66.78                      | 4.55              |

### TABLE 3 Classification of risk mitigation, online simulation

| Class       | Sub class | Description                                                                 |
|-------------|-----------|-----------------------------------------------------------------------------|
| Mitigated   | NR        | \( r_{\text{risk}} = 0 \) & \( r_{\text{risk}}^2 = 0 \)                   |
| Mitigated   | RM        | \( r_{\text{risk}} > 0 \) & \( r_{\text{risk}}^2 = 0 \)                   |
| Remained    | RD        | \( r_{\text{risk}} > 0 \) & \( r_{\text{risk}}^2 < r_{\text{risk}} \)   |
| Remained    | RI        | \( r_{\text{risk}} > 0 \) & \( r_{\text{risk}}^2 > r_{\text{risk}} \)   |
| Remained    | RR        | \( r_{\text{risk}} > 0 \) & \( r_{\text{risk}}^2 = r_{\text{risk}} \)   |

### TABLE 4 Energy delivery and financial data BWF

\[ (1.2) \times £/MWh \]
The application of the seven hypothetical WFO is tested for each location, considering the corresponding water temperature profiles in Figure 2, while the hours ahead thermal risk estimation and online power curtailment are applied.

The total percentage of mitigated and remained risk after curtailment for each WFO scenario are summarised in Figures 8 and 9 for the case of L1 and L2, respectively.

The higher preceding of risk mitigated in WFO5 compared to WFO4 are related to the assumptions made for the curtailment strategy. To avoid thermal overheating, a curtailment action is trigged if the likely pdf\(\hat{T}(t)\) calculated for the 6 h ahead exceeds \(90^\circ C\). The load current \(I(t)\) is reduced for one hour, while, the next time step considers the curtailed \(I_{\text{BF}6}: (t + 1)\) as a starting point to evaluate the next thermal risk 6 h ahead. If further risk is estimated a second hour curtailment is applied.

A more conservative approach could be applied by reducing \(T_{\text{limit}}\) so that curtailment power is triggered at a lower temperature, that is, \(T_{\text{limit}} = 87^\circ C\). Another alternative for

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**FIGURE 6** Conductor temperature profiles, L1

**FIGURE 7** Conductor temperature profiles, L2

**FIGURE 8** Mitigated and remaining thermal risk after curtailment, L1

**FIGURE 9** Mitigated and remaining thermal risk after curtailment, L2

**4.1 Percentage of mitigated thermal risk**
the same purpose is the application of an optimised curtailment strategy i.e. extending the periods of power curtailment, $I_{WF}(t + 2)$. These are parameters that can be adjusted by the user needs and can potentially improve the thermal risk mitigation results.

Tables 5 and 6 present the percentages of NR, RM, RD, RI, RR as per Table 3 for the two thermal sections of the cable. The results reflect that for both offshore locations, no percentage of thermal risk was induced until WFO4.

4.2 Thermal risk severity analysis

Given the importance of avoiding thermal damage in the cable, a severity analysis was carried out considering the remaining risk percentages for the corresponding cases in Figures 8 and 9. The conductor temperature exceedance involved were gathered over the simulation year, and the results are presented in Figures 10 and 11.

The most extreme values of temperature over 90$^\circ$C (excluding outliers) correspond to WFO7; almost reaching 1.4$^\circ$C over the temperature limit for the case of L1 and 0.7$^\circ$C for the case of L2. An overview of all the thermal exceedance reflects that the mean average values of temperature exceedance (red line) are within 1$^\circ$C for all the WFO cases.

The calculated severity of thermal exceedance would not represent damage to the cable as the ageing behaviour of XLPE is not an instantaneous process but a gradual deterioration of the material properties when operated over its maximum temperature limit for long periods. Thus, as the average operating

**TABLE 5** Results risk mitigation, L1

| WFO | NR$_{L1}$ | RM$_{L1}$ | RD$_{L1}$ | RI$_{L1}$ | RR$_{L1}$ | NR$_{L1}$ | RM$_{L1}$ | RD$_{L1}$ | RI$_{L1}$ | RR$_{L1}$ |
|-----|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| 1   | 100      | 0        | 0        | 0        | 0        | 100      | 0        | 0        | 0        | 0        |
| 2   | 100      | 0        | 0        | 0        | 0        | 100      | 0        | 0        | 0        | 0        |
| 3   | 100      | 0        | 0        | 0        | 0        | 100      | 0        | 0        | 0        | 0        |
| 4   | 98.25    | 0.50     | 0.30     | 0.06     | 0.86     | 100      | 0        | 0        | 0        | 0        |
| 5   | 76.64    | 23.27    | 0.05     | 0.02     | 0.01     | 100      | 0        | 0        | 0        | 0        |
| 6   | 69.05    | 30.88    | 0.06     | 0        | 0        | 92.39    | 7.60     | 0        | 0        | 0        |
| 7   | 63.57    | 16.93    | 8.40     | 0        | 11.08    | 82.25    | 17.74    | 0        | 0        | 0        |

**TABLE 6** Results risk mitigation, L2

| WFO | NR$_{L2}$ | RM$_{L2}$ | RD$_{L2}$ | RI$_{L2}$ | RR$_{L2}$ | NR$_{L2}$ | RM$_{L2}$ | RD$_{L2}$ | RI$_{L2}$ | RR$_{L2}$ |
|-----|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| 1   | 100      | 0        | 0        | 0        | 0        | 100      | 0        | 0        | 0        | 0        |
| 2   | 100      | 0        | 0        | 0        | 0        | 100      | 0        | 0        | 0        | 0        |
| 3   | 100      | 0        | 0        | 0        | 0        | 100      | 0        | 0        | 0        | 0        |
| 4   | 88.71    | 8.39     | 2.22     | 0.39     | 0.26     | 100      | 0        | 0        | 0        | 0        |
| 5   | 74.83    | 25.16    | 0        | 0        | 0        | 100      | 0        | 0        | 0        | 0        |
| 6   | 66.68    | 26.61    | 6.69     | 0        | 0        | 97.72    | 2.27     | 0        | 0        | 0        |
| 7   | 60.65    | 29.81    | 9.52     | 0        | 0        | 83.60    | 16.39    | 0        | 0        | 0        |
temperature of XLPE is kept under 90°C, mild instantaneous incidences of < 1.5°C over the limiting temperature would not represent a problem for the cable and would be within the ranges experienced during qualification testing.

4.3 Conductor temperature estimation

The annual cable thermal profile corresponding to WFO4 (L1) in Figure 12 shows how the preventive curtailment can keep the conductor temperature limit with some instances above 90°C not higher than 0.2°C as demonstrated in Figure 10. Additionally, the conductor temperature profile throughout December is presented in Figure 13 for WFO4 and Figure 14 for WFO5 along with the 5th and 95th percentiles of the estimated 6 h ahead distribution of temperature $pdf_{T(t)}$ represented by the yellow-coloured area.

Similarly, the annual thermal profile corresponding to WFO4 (L2) is shown in Figure 15 were the instances above 90°C were not higher than 0.6°C (see Figure 11). Figures 16 and 17 present thermal profiles from the month of May along with the 5th and 95th percentiles of the estimated 6 h ahead distribution of temperature $pdf_{T(t)}$ represented by the yellow-coloured area. The 5th and 95th percentile values from $pdf_{T(t)}$ are plotted 6 h ahead thus reflects how the methodology can estimate the likely future load current and cable temperature utilising ramp events identification and evaluation. The selected two different periods of the year demonstrate the ability of the ramp based TRE
4.4 Energy delivery and economic benefits

The application of WFO allows an increased energy delivery due to the extra installed capacity however the online thermal risk estimation and curtailment applied by the proposed methodology will generate a cost of energy losses due to power curtailment which must be avoided. For instance, an economic analysis of the additional power gathered by the WFO along the computation of the curtailed energy is used to estimate the additional annual revenue and estimated LCOE_cable part to determine the optimal overplanting scenario.

Table 7 (L1) and Table 8 (L2) present the calculated amount of energy delivered/curtailed as well as the approximate revenue over the testing year compared to the static rating limits used to calculate the base BWF rating.

A visual representation of the economic analysis is given in Figures 18 and 19 in which the top part of the figures represents the amount of energy that was transferred through the cable (GWh/year) considering the corresponding WFO case and curtailment actions (blue line) while the corresponding
revenue (million £/year) is represented by the red line. The bottom part of the figures presents the amount of energy curtailed (GWh/year) to avoid exceeding the allowed temperature limit of 90°C.

Accordingly, the red line on the bottom of the figures represents the approximate cost of the power curtailment involved in each WFO case. The pink dotted lines in Figures 18 and 19 represent the optimal WFO case for each location which is selected as the most economically beneficial considering the maximum increment in power delivery with a minimum power curtailment which will allow reducing the LCOE compared to the base wind farm.

The approximate energy delivered and curtailed are used to calculate the LCOE\textsubscript{cable} part according to Equation (7) and the results are shown in Figures 20 and 21. The reduction in the LCOE\textsubscript{cable} is evident until the amount of curtailment applied by the methodology increases to the point where the LCOE would be higher than the BWF scenario.

Figure 20 shows that the optimal overplanting cases considering variable water temperature simulations were found to
FIGURE 17  Cable temperature profile WFO5 (blue) and estimated temperature 6h ahead (yellow) during May, L2

TABLE 7  Results financial assessment, L1

| WFO | Energy GWh/year | Approximate revenue £MWh/year | Additional energy MWh/year | Additional gross revenue £MWh/year | Curtailed energy MWh/year | Curtailment cost £MWh/year |
|-----|-----------------|-------------------------------|---------------------------|-----------------------------------|---------------------------|-----------------------------|
| BWF | 962.96          | 69.81                         | 0                         | 0                                 | 0                         | 0                           |
| 1   | 1004.83         | 72.85                         | 41.86                     | 3.03                              | 0                         | 0                           |
| 2   | 1046.7          | 75.88                         | 83.73                     | 6.07                              | 0                         | 0                           |
| 3   | 1088.57         | 78.92                         | 125.60                    | 9.1                               | 0                         | 0                           |
| 4   | 1130.31         | 81.94                         | 167.34                    | 12.13                             | 128                       | 9,280                       |
| 5   | 1142.13         | 82.8                          | 179.16                    | 12.98                             | 3,008                     | 2,180,800                   |
| 6   | 1156.50         | 83.84                         | 193.53                    | 14.03                             | 5,808                     | 4,210,800                   |
| 7   | 1173.11         | 85.05                         | 210.15                    | 15.23                             | 85,232                    | 6,179,320                   |

TABLE 8  Results financial assessment, L2

| WFO | Energy GWh/year | Revenue million £MWh/year | Additional energy MWh/year | Additional gross revenue £MWh/year | Curtailed energy MWh/year | Curtailment cost £MWh/year |
|-----|-----------------|---------------------------|---------------------------|-----------------------------------|---------------------------|-----------------------------|
| BWF | 921.2           | 66.78                     | 0                         | 0                                 | 0                         | 0                           |
| 1   | 963.07          | 69.82                     | 41.87                     | 3.03                              | 0                         | 0                           |
| 2   | 1,004.9         | 72.85                     | 83.74                     | 6.07                              | 0                         | 0                           |
| 3   | 1,046.82        | 75.89                     | 125.61                    | 9.1                               | 0                         | 0                           |
| 4   | 1,084.74        | 78.64                     | 163.53                    | 11.85                             | 2,976                     | 215,760                     |
| 5   | 1,093.4         | 79.27                     | 172.2                     | 12.48                             | 30,112                    | 2,183,120                   |
| 6   | 1,106.99        | 80.25                     | 185.79                    | 13.46                             | 56,400                    | 4,089,000                   |
| 7   | 1,113.27        | 80.71                     | 192.06                    | 13.92                             | 90,528                    | 6,563,280                   |
be WFO4 with a financial benefit of approximately £12.13 million/year which contributed to reducing the calculated $LCOE_{cable}$ by £0.64/MWh for L1. Similarly, for L2, Figure 21 shows WFO4 as the optimal overplanting scenario allowing a financial benefit of approximately £11.85 million/year which could reduce the energy price by £0.48/MWh for the present cable length and capital cost.

5 | CONCLUSION

The results of the thermal risk estimation generated by the proposed algorithms combined with a curtailment strategy can increase the amount of power transferred by the cable system while minimising the risk of exceeding the cable temperature limit. The additional power delivered could represent an increment of energy sales and a contribution to reducing the overall cost of energy generated offshore.

The study presented in this paper along with the ramp identification methodology for the hours ahead TRE demonstrate the capacity of submarine export cables to transfer higher ratings than the static rating limits traditionally imposed as per IEC standards. For instance, considering a modest wind farm overplanting increment of WFO3 the power delivered was 1088.5 GWh/year which is 13.0% more than BWF in L1 and 1046.8 GWh/year, which is 13.6% compared to BWF in L2.
without any risk of exceeding the cable temperature limit and no need for energy curtailment (see Tables 7 and 8).

On the other hand, if a rating increment of WFO4 is allowed the annual energy delivery is 1130.3 GWh/year which is 17.4% more than BWF in L1 and 1,084.7 GWh/year which represents a 17.7% increment over BWF in L2 with a risk of thermal overheating of 1.2% and 2.8%, respectively. However, this scenario relying on a certain amount of preventive power curtailment to avoid cable thermal overheating while the remaining incidents of thermal exceedance are within 0.6°C above the allowed 90°C. The calculated severity of thermal exceedance would not cause damage to the cable as the ageing behaviour of XLPE is not an instantaneous process and the size of the exceedance is small, typically $\approx 1^\circ$C.

### 6 | DISCUSSION

The novel methodology developed in this paper is an example of the use of Bayesian reasoning to develop simple but reliable algorithms to solve non-linear/stochastic problems. The importance of targeting toward simples design can be further illustrated in [38–40] where the use of Markov Chain, Fuzzy Logic, MCS are used in the modelling and control of stochastic plasma for fusion energy applications.

The proposed cable system is a simplified example considering landfall and submarine cable sections. The cable system, thermal model and ambient parameters can be adapted to suit specific conditions, for instance, a variable temperature profile could be added into the framework.

The cable model is not an extension of the proposed methodology thus the method can work with any thermal model and specific cable system that the user may have. The use of two different thermal sections exemplifies how the methodology can be applied to “k” sections of the cable in a parallel analysis to track the thermally limiting cable parts.

Regarding charging current, the model can be deployed at any point along the cable and thus the charging current must be calculated and added to the load current profile depending on operating voltage, cable length, location of the reactive
compensation. The addition of reactive current in the dataset would increase the load current profile which would not affect the ramp rate study algorithm or the thermal risk estimation process.

The proposed offline TRE could be used during the early stages of project development to simulate over-planting increments and evaluate the reduction of export cable sizes or cable rating increments. On the other hand, the online TRE methodology is intended as a decision-making tool that can be used by the TSO to plan and perform power curtailment based on an estimated hour ahead thermal overview of the cable.

Additional conservatism can be induced in the estimations by reducing the allowed $T_{limit}$ in the algorithm which will act as a safety margin to the cable installation and would help to further reduce the remaining risk for the online application of the methodology. Another alternative for the same purpose is the application of an optimised curtailment strategy, that is, extending the periods of load current reduction in the online TRE algorithm.

**Nomenclature**

**BWEX** Base wind farm

**CAPEX** Capital expenditure

$C_{cable}$ Capital cost of the export cable

**CiD** Contracts for difference

CRF Annual capital recovery factor

$E_{curtailed}$ Annual cost of energy losses due to curtailment

$E_{WFO}$ Annual amount of energy sold (MWh)

FDM Finite difference model

FDM$_{main}$ Main part of the TRE algorithm that calculates real time cable temperatures

FDM$_{sub}$ Subroutine of the TRE algorithm that estimate hours ahead cable temperatures

L1 Location one, Dogger Bank wind-farm licence area

L2 Location two, Star of the South Wind Farm licence area

LCOE Levelised cost of energy

MAD Median absolute deviation

MCS Monte Carlo simulation

**MERRA** Modern era retrospective-analysis for research and applications

NR No risk

NW North-west

RD Risk decreased

RI Risk increased

RM Risk mitigated

RR Risk remained

S1 Submarine cable section $800^2_{nom}$

S2 Landfall cable section $1400^2_{nom}$

TRE Thermal risk estimation

TS1 Training set 1

TS2 Training set 2

TSO Transmission system operator

WFO Wave farm over-planting

WT Wind turbine

XLPE Cross-linked polyethylene

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**REFERENCES**

1. IEC, I.E.C.: IEC 60287-1: Electric cables—Calculation of the current rating, Part 1: Current rating equations (100% load factor) and calculation of losses-General. (2014)

2. Wallkorf, S.P., John, S., Hoppe, F.J.: The use of real-time monitoring and dynamic ratings for power delivery systems and implication for dielectric materials. IEEE Electr. Insul. Mag. 15(5), 28–33 (1999)

3. Wolter, C., et al.: Overplanting in offshore wind power plants in different regulatory regimes. In: 15th Wind Integration workshop—International Workshop on Large-Scale Integration of Wind Power into Power Systems as well as on Transmission Networks for Offshore Wind Power Plants, pp. 1–8 (2016)

4. Blavette, A., et al.: Dimensioning the equipment of a wave farm: Energy storage and cables. IEEE Trans. Ind. Appl. 51(3), 2470–2478 (2015)

5. Pilgrim, J.A., Kelly, S.: Thermal and economic optimisation of wind-farm export cable. In: IET Renewable Power Generation 2018, Lyngby, Denmark, pp. 1–6

6. Michiorri, A., et al.: Forecasting for dynamic line rating. Renew. Sustainable Energy Rev. 52, 1713–1730 (2015)

7. Jupe, S., Bartlett, M., Jackson, K.: Dynamic thermal ratings: The state of the art. In: CIRED 21st International Conference on Electricity Distribution, pp. 1–4 (2011)

8. Jupe, S.C.E., et al.: Application of a dynamic thermal rating system to a 132kV distribution network. In: IEEE PES Innovative Smart Grid Technologies Conference Europe, pp. 1–8 (2011)

9. Michiorri, A., Taylor, P.C.: Forecasting real-time ratings for electricity distribution networks using weather forecast data. In: 20th International Conference on Electricity Distribution CIRED, pp. 1–4 (2009)

10. Morrow, D.J., Fu, J., Abdelkader, S.M.: Experimentally validated partial least squares model for dynamic line rating. IET Renew. Power Gener. 8(3), 260–268 (2014)

11. Anders, G.J., Brakelmann, H.: Rating of underground power cables with boundary temperature restrictions. IEEE Trans. Power Deliv. 33(4), 1895–1902 (2018)

12. Catmull, S., et al.: Cyclic load profiles for offshore wind farm cable rating. IEEE Trans. Power Deliv. 31(3), 1242–1250 (2016)

13. Matine, A., et al.: Optimal sizing of submarine cables from an electro-thermal perspective. In: European Wave and Tidal Conference (EWTEC), 2017, Cork, Ireland, pp. 1–8

14. Shanky, F., et al.: Dynamic electrical ratings and the economics of capacity factor for wave energy converter arrays. In: Proceedings of the 9th European Wave and Tidal Energy Conference, pp. 1–8 (2011)

15. Exizidis, L., et al.: Thermal behavior of power cables in offshore wind sites considering wind speed uncertainty. Appl. Therm. Eng. 91, 471–478 (2015)

16. Kvarts, T., et al.: Systematic description of dynamic load for cables for offshore wind farms. Method and Experience. In: International Council on Large Electric Systems (Cigre), 2016, Paris, France pp. 1–12

17. Gallego-Castillo, C., Caerva-Tejero, A., Lopez-Garcia, O.: A review on the recent history of wind power ramp forecasting. Renew. Sustainable Energy Rev. 52, 1148–1157 (2015)

18. Nayak, A.K., et al.: ARIMA based statistical approach to predict wind power ramps. In: 2015 IEEE Power and Energy Society General Meeting, pp. 1–5.IEEE, Piscataway, NJ (2015)
19. Sevlian, R., Rajagopal, R.: Detection and statistics of wind power ramps. IEEE Trans. Power Syst. 28(4), 3610–3620 (2013)
20. Ma, H., Liu, Y.: Real-time recognition of wind power ramp events. In: 2nd IET Renewable Power Generation Conference (RPG 2013), pp. 1–4.IEEE, Piscataway, NJ (2013)
21. Cui, M., et al.: Wind power ramp event forecasting using a stochastic scenario generation method. IEEE Trans. Sustainable Energy 6(2), 422–433 (2015)
22. Zareipour, H., Huang, D., Rosehart, W.: Wind power ramp events classification and forecasting: A data mining approach. In: IEEE Power and Energy Society General Meeting, pp. 1–3.IEEE, Piscataway, NJ (2011)
23. Yang, L., et al.: Support-vector-machine-enhanced markov model for short-term wind power forecast. IEEE Trans. Sustainable Energy 6(3), 791–799 (2015)
24. Ganger, D., Zhang, J., Vittal, V.: Statistical characterization of wind power ramps via extreme value analysis. IEEE Trans. Power Syst. 29(6), 3118–3119 (2014)
25. Colin, M.A.H., Pilgrim, J.A.: Cable thermal risk estimation for overplanted wind farms. IEEE Trans. Power Deliv. 35(2), 609–617 (2020)
26. Hernandez Colin, M.A., Pilgrim, J.A.: Assessment of financial benefits in overplanted wind farm export cable. In: 10th International Conference on Insulated Power Cables (jicable), pp. 1–6 (2019)
27. Hughes, T.J., et al.: Effect of sediment properties on the thermal performance of submarine HV cables. IEEE Trans. Power Deliv. 30(6), 2443–2450 (2015)
28. Dix, J.K., et al.: Substrate controls on the life-time performance of marine HVACables. In: Smarter Solutions for Future Off shore Developments, pp. 88–107 (2017)
29. Rienecker, M.M., et al.: MERRA: NASA’s modern era retrospective analysis for research and applications. J. Climate 24, 3624–3648 (2011)
30. National Astronautics and Research Administration: Global Modelling and Assimilation Office (2017). https://gmao.gsfc.nasa.gov/reanalysis/MERRA/
31. Hernandez Colin, M.A., Pilgrim, J.A.: Offshore cable optimization by probabilistic thermal risk estimation. In: 2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), pp. 1–6.IEEE, Piscataway, NJ (2018)
32. Tonani, M., et al.: North West European Shelf Production Centre, Technical Report (2017)
33. Wijeratne, S., Pattiaratchi, C., Proctor, R.: Estimates of surface and subsurface boundary current transport around Australia. J. Geophys. Res.: Oceans 123(5), 3444–3466 (2018)
34. Anders, G., Georgallis, G.: Transient analysis of 3-core SL-type submarine cables with jacket around each core. In: International Conference on Insulated Power Cable (jicable), pp. 1–6 (2015)
35. Mone, C., et al.: 2017 Cost of Wind Energy Review, Technical Report (2018, September)
36. Estate, T.C., Renewable, O., Catapult, E.: Guide to an offshore wind farm. Technical Report (2019, January)
37. Department for Business Energy & Industrial Strategy: Contracts for Difference (CfD) Allocation Round 3: results (2019). https://www.gov.uk/government/publications/contracts-for-difference-cfd-allocation-round-3-results/contracts-for-difference-cfd-allocation-round-3-results
38. Rastovic, D.: On stochastic control of tokamak and artificial intelligence. J. Fusion Energy 26(4), 337–342 (2007)
39. Rastovic, D.: Fractional Fokker–Planck equations and artificial neural networks for stochastic control of tokamak. J. Fusion Energy 27(3), 182–187 (2008)
40. Rastovic, D.: From non-Markovian processes to stochastic real time control for tokamak plasma turbulence via artificial intelligence techniques. J. Fusion Energy 34(2), 207–215 (2015)

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