On the complementarity of wave, tidal, wind and solar resources in Ireland

Hafiz Ahsan Said, Shaun P. Costello, and John V. Ringwood

Abstract—**This paper presents a complementarity assessment of the four renewable resources, i.e. wave, tidal, wind and solar, around the Island of Ireland (including Northern Ireland). A particular focus is given to the potential benefits of combining relatively unexploited but significant marine renewable energy resources (wave and tidal) in Ireland, with more established renewable technologies, such as wind and solar. New complementarity metrics, based on the mathematical principle of total variations, variance and standard deviation, are utilised here, since they can be used to assess the complementarity of more than two resources. The results show clear benefits of diversifying the resource mix with the highest complementarity achieved for combining all four resources.**

Index Terms—**Complementarity, combined renewable resources, wave energy, wind energy, Ireland**

I. Introduction

THE use of renewable energy sources has been recognised as a key strategy for combating anthropogenic climate change. These energy sources are regarded as sustainable because they are naturally replenished and do not produce greenhouse gases. A vital step in achieving a low-carbon economy and addressing the global challenge of climate change is the implementation of renewable energy alternatives. This *green revolution* has been led by solar and wind energy. Incorporating new forms of renewable energy resources, such as wave and tidal energy, into the current mix of resources will aid in the transition to a fully 100% renewable energy future, due to the abundance of such resources [1]. Utilising a combination of resources will improve the reliability of the energy supply system and lower the cost of incorporating renewable energy into the current generation mix.

The concept of energetic complementarity refers to the ability of multiple variable renewable energy sources to work together synergistically to increase the reliability of the system, thereby reducing the occurrence of periods with a shortfall in energy generation. The complementarity assessment of renewable energy resources is crucial to the design of the optimal mix of these resources to meet load requirements in a jurisdiction. Multiple studies in the literature discuss the complementarity of renewable energy modalities for different jurisdictions. A review of such studies is presented in [2]. The review shows that most of these studies focus on wind, solar and hydro-power generation, with most focusing on just two of these three modalities. For example, the complementarity, for various jurisdictions, of wind and solar is studied in [3]–[5], wind and wave resource complementarity is studied in [6], [7] and solar and hydro complementarity is studied in [8], [9]. However, recent efforts have been made to assess the temporal complementarity of more than two resources, including marine renewable energy resources (wave and tidal) for US and UK jurisdictions [10], [11], concluding that marine renewable resources may have significant value to future power systems in terms of reduced balancing requirements and valuable capacity contribution.

Similarly, Ireland may enjoy similar benefits from combined resource exploitation, due to its island topography and enviable marine resource. By way of example, Fig. 1 presents renewable resource generation profiles (hourly resolution) for four seasonal weeks in 2017 and illustrates the potential benefits of combining marine resources at Inishtrahull Sound, Ireland. In particular, the highlighted sections in Fig. 1 point out the times of the week when at least one resource is unavailable, but others are available and provide complementary benefits. For example, wind and tidal are low in the autumn week (highlighted section), while wave and solar resources are available. However, the summer week sees low wind and wave resources, while tidal and solar provide complementary benefits.

Another critical aspect of the complementarity studies is the set of metrics and indices used to assess complementarity. Correlation coefficients are commonly used in the literature to evaluate complementarity between energy sources. However, several issues arise with the correlation metrics reported in the literature, including the inability to handle nonlinearities in the data and the inability to handle more than two resources at a time [12], to name a few. In addition to correlation, Beluco et al. [9] introduced a complementary metric calculated by combining three partial indices. The first index, the partial time complementarity index, measures the time interval between the minimum values of two sources. The second index, the partial energy complementarity index, evaluates the relationship between the average values of two sources. The third index, the partial amplitude complementarity index, assesses the differences between the maximum and minimum values of the two energy sources. However, this metric may

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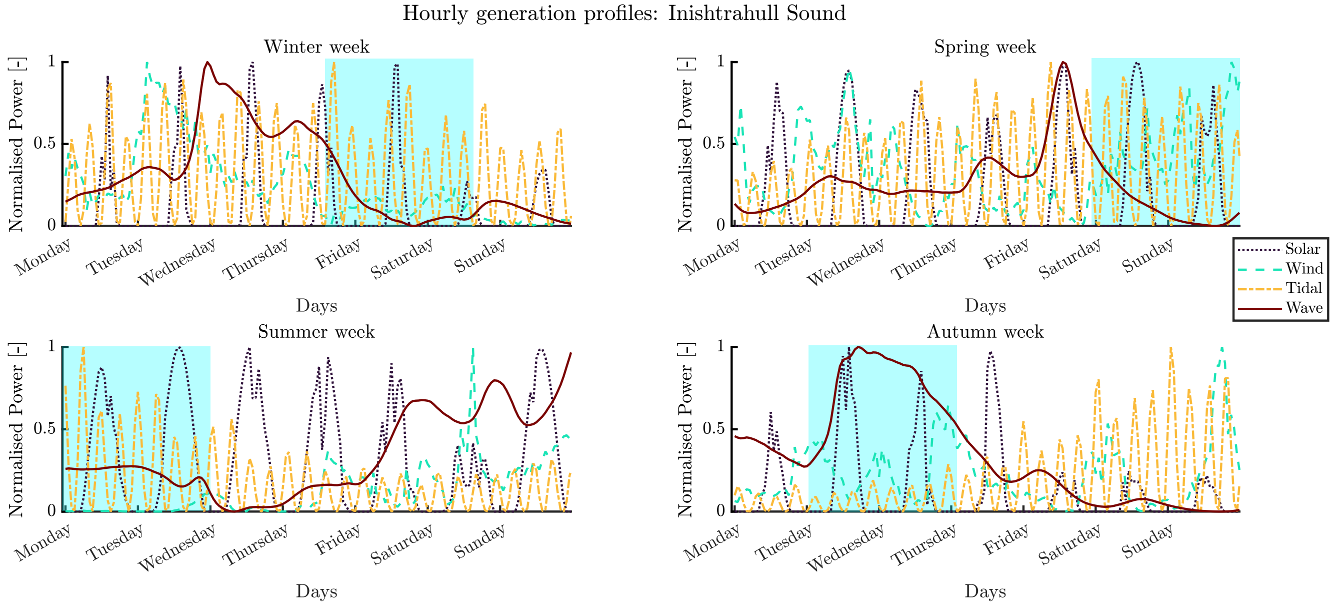

Fig. 1. Time series plot of normalised raw power available near Inishtrahull Sound for four different seasonal weeks of 2017. In the plots, highlighted sections indicate times of the week when complementarity benefits of combined resource exploitation may be gained.

not work effectively for complex series beyond simple annual sinusoidal patterns. A detailed review of such complementarity metrics and indices is presented in [13].

In this paper, we present a complementarity assessment of the four renewable resources, i.e. wave, tidal, wind and solar, around the island of Ireland (including Northern Ireland), using new complementarity indices based on the mathematical concepts of total variation, variance and standard deviation [12], which allow for complementarity assessment of more than two resources. We also comment on the possible benefits of the temporal characteristics of the marine renewable resources in the Irish generation mix.

The remainder of the paper is organised as follows: Section II describes the data collection and power generation profiles for all four resources, and Section III details the methodology used here to assess complementarity, including various complementarity indices used. Results and discussions are presented in Section IV, while Section V concludes this study.

II. Data Collation and Power Generation

A. Choice of data location points around Ireland

To assess the potential of the four resources mentioned above, the first crucial step is to gather relevant data. In this study, the selection of data locations is based on identifying potential tidal sites around the Island of Ireland, since this is the limiting factor, over wind, solar and wave, which are present in most Irish coastal locations. These chosen locations can be visualised in Fig. 2, where they are represented by coloured circles. By opting for the same locations for each resource, there are several advantages, such as the possibility of co-located power plants that can leverage shared electrical infrastructure and other synergies. The data for each resource was obtained from two

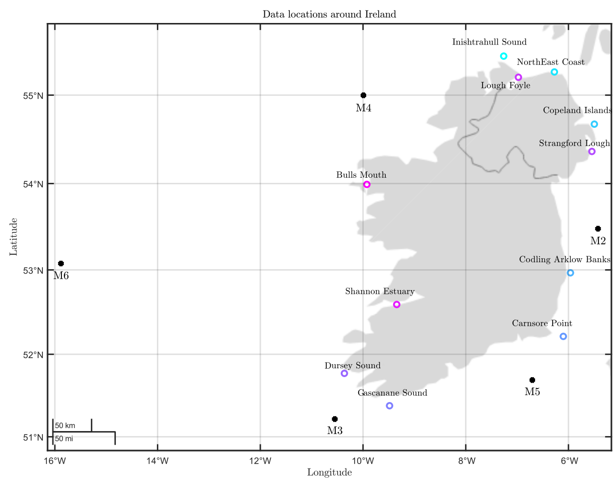

Fig. 2. Data collection locations around Ireland considered in this study.

primary sources: the Marine Institute [14], and a high-resolution solar and wind dataset provided in [15]. It is important to note that the data from these two sources could only be obtained for a single overlapping year, which, in this case, is 2017.

The Marine Institute served as the primary source for tidal and wave data. However, it was found that the wave dataset provided by the Marine Institute for the nominated tidal locations (as shown in Fig. 2) was not suitable due to the influence of wind on tide effects [16], i.e. waves generated as a result of wind against tide, at these tidal locations. As a result, additional wave data was collected from the ERA5 database [17], specifically for locations further offshore, as shown by black dots (M2-M6) in Fig. 2. These additional wave data points were incorporated to enhance the comprehensiveness of the complete dataset. It is worth noting that all the datasets are modelled data, albeit

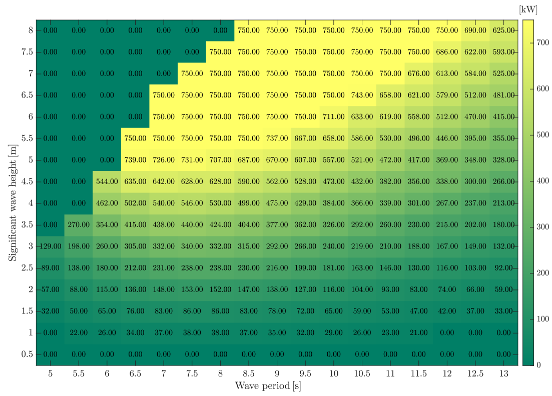

Fig. 3. Power matrix for the 750 kW Pelamis WEC [19]

validated against different metrics, thereby avoiding local wind-on-tide effects in the measured data.

B. Wave data and power generation

As mentioned in Section II, the ERA5 database provides wave data for this project, including mean wave period T_m and significant wave height H_s. The data was resolved on an hourly basis, and an hourly time series covering an entire year (2017) was provided, representing one data point for each of T_m and H_s at each hour.

Computing the extracted power from wave energy devices presents challenges due to the lack of standardised wave technology and the diverse operating principles of available devices [18]. Consequently, establishing a uniform measure of the extracted power for wave energy remains challenging. In this study, the 750 MW Pelamis wave energy converter (WEC) [19], has been chosen as the reference device, due to its well-documented power production characteristics. The power production of the Pelamis converter is described in a published power matrix, as depicted in Fig. 3, which, though subject to generic concerns regarding power matrix representations [20], provides a reliable basis for analysis and comparison in this study with simplicity and computability as priorities.

C. Tidal data and power generation

Tidal data, provided by the Marine Institute, was given as an hourly time series covering one year. The provided parameters included surface current velocities in the eastward direction (u) and northward direction (v), as well as depth-averaged velocities in those directions.

The conversion of tidal stream kinetic energy into electrical power requires the installation of tidal devices. In this current article, the tidal devices employed are similar to marine versions of well-established horizontal-axis wind turbines. The instantaneous kinetic energy available in the tidal stream can be expressed as $P_c(t) = \frac{1}{2}A_t v^3(t)$, where $r = 1030$ kg/m^3 represents the density of seawater, $A_t = 10$ [m] denotes the cross-sectional area swept by the rotor, and $v(t)$ denotes the velocity of the water stream. The tidal

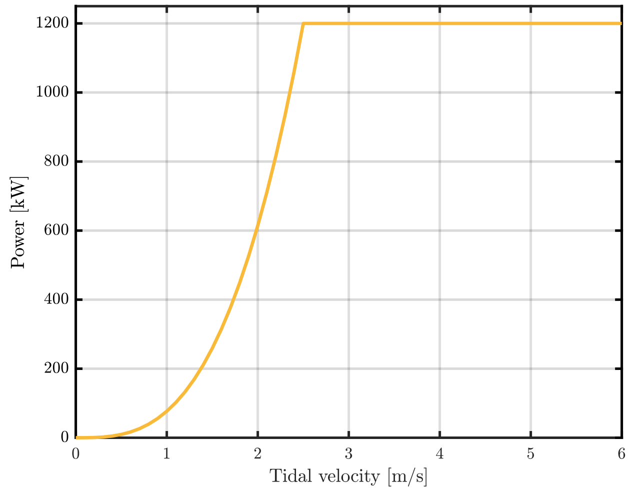

Fig. 4. Tidal turbine curve utilised in this study.

turbine is capable of harnessing only a portion of this energy, contingent upon its technical characteristics, as given below:

$$P_{\text{tidal}} = C_p P_c, \tag{1}$$

where C_p represents the power coefficient, which is a function of blade pitch angle and tip speed ratio. A $C_p = 0.45$ is assumed here [21]. The resultant power curve for the tidal device is presented in Fig. 4

D. Wind data and power generation

Wind data, provided by the authors of [15], is also in the form of an hourly time series, and wind is a less predictable energy source than solar or tidal. The selection of various locations across Ireland mitigates direct correlation in the available wind power by offering spatial diversity, although some correlation still persists. While individual weather systems can span the entire island, this spatial diversity contributes to the consistent and reliable utilisation of wind power. However, it should be noted that large weather systems generally entail some degree of direct correlation between different locations. In relation to the power

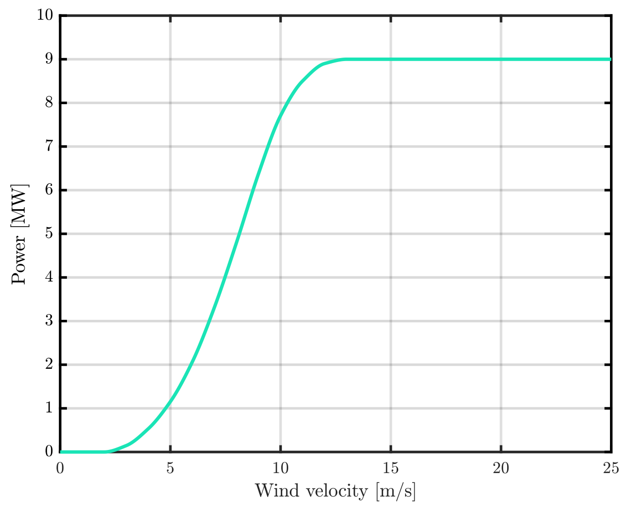

Fig. 5. Wind turbine curve utilised in this study.

extracted from wind, the maturity of wind turbine technology enables the utilisation of well-established power curves. For this study, a representative W2E-215/9.0 (9MW) [22] wind turbine is selected, with the associated power curve depicted in Fig. 5.

E. Solar data and power generation

Solar data, with hourly resolution, is also made available by the authors of [15] for 2017. Similar to the tidal data, the solar data exhibit a high level of predictability, following a diurnal pattern with the highest solar irradiance levels occurring in the summer, as expected.

The generation of solar power (P_{solar}), from a photovoltaic generator at a specific time t, relies on the global solar irradiance (G_{irr}) and the air temperature (T_{air}) [3]. This relationship can be expressed [23] using:

$$P_{\text{solar}} = \eta_p G_{\text{irr}}(t) \left[1 - \mu(T_{\text{air}} - T_{\text{STC}}) - \mu C G_{\text{irr}}(t)\right], \quad (2)$$

where η_p represents a constant production parameter, which is the product of PV array surface area and inverter (and generator) efficiencies. μ and C are the efficiency reduction factors depending on the temperature and irradiance, respectively. T_{STC} is the standard test condition temperature corresponding to the photovoltaic cell [24].

III. Methodology

When evaluating the complementarity of all four resources, traditional correlation-based metrics are not applicable. To address this limitation, new complementarity metrics have been proposed in [12]. These metrics offer the advantage of assessing complementarity among more than two resources. Each metric is detailed in the following subsections.

A. Total variation complementarity index

This index is based on the mathematical concept of *total variations*. For n functions f_i, $\forall\ i = 1, 2, \ldots, n$, the generalised formulation of the total variation complementarity index, over a time interval $[a, b]$, can be expressed as:

$$\Phi(f_i) = 1 - \frac{\bigvee_b^a (f_1 + f_2 + \cdots + f_n)}{\bigvee_b^a (f_1) + \bigvee_b^a (f_2) + \cdots + \bigvee_b^a (f_n)}, \quad (3)$$

with,

$$\bigvee_b^a = \sup \sum_{j=1}^{m} |f(t_j) - f(t_{j-1})|, \quad (4)$$

defined as the total variation of a function $f(t)$. The supremum is taken over all possible finite partitions $a = t_1 < \ldots < t_n = b$ of $[a, b]$. It is evident that the value of the complementarity metric $\Phi(f_i)$ falls within the range of 0 to 1, where $\Phi(f_i) = 1$ indicates perfect complementarity, and $\Phi(f_i) = 0$ represents no complementarity (similar to high level of correlation). Φ is sensitive to the scale of the variables, requires persistence of the series (not just their cross-correlation), and is applicable to more than two variables. For a comprehensive discussion on the characteristics of this metric, readers are referred to [12].

B. Variance complementarity index

In this metric, Eq. (3) can be adapted by replacing the total variation with variance (σ^2). By considering the variance, the metric takes into consideration the variability and spread of the variables, providing a more appropriate assessment of complementarity, compared to correlation.

$$\Phi_v(f_i) = 1 - \frac{\sigma^2(f_1 + f_2 + \cdots + f_n)}{\sigma^2(f_1) + \sigma^2(f_2) + \cdots + \sigma^2(f_n)}, \quad (5)$$

where $-1 < \Phi_v < 1$. For consistent analysis, Φ_v is rescaled as follows:

$$\hat{\Phi} = \frac{(\Phi_v + 1)}{2}, \quad (6)$$

where $0 < \hat{\Phi} < 1$. Originally, $\hat{\Phi}$ is intended for only two resources by fixing the above-mentioned definition to two timeseries, resulting in a correlation-based metric [12]. However, in this paper, we use the generalised definition presented in (5), and use this metric to calculate complementarity among all four resources.

C. Standard deviation complementarity index

Similar to the variance complementarity index, the standard deviation complementarity index, denoted by Φ_s, is obtained by replacing the total variation in (3) by the standard deviation σ, as:

$$\Phi_s(f_i) = 1 - \frac{\sigma(f_1 + f_2 + \cdots + f_n)}{\sigma(f_1) + \sigma(f_2) + \cdots + \sigma(f_n)}, \quad (7)$$

where $0 < \Phi_s < 1$. Φ_s measures the variability of the sum using standard deviation, thereby maintaining the same dimension as the original variables, unlike the squared values in Φ_v.

IV. Results and discussion

To demonstrate the potential complementarity among resources, the proposed metrics are calculated for various locations throughout Ireland, using different time scales, and combinations of resources. All three complementarity indices, namely Φ, Φ_s, and $\hat{\Phi}$, are used for the analysis. Furthermore, the time-series data for each resource is normalised to its maximum value, ensuring a consistent scale for complementarity assessment. This normalisation process facilitates a fair comparison and evaluation of complementarity among the different resources.

Table I presents the complementarity among all resources (raw data) for 2017, categorised by location. The table illustrates that the complementarity among the four resources remains relatively consistent across all locations, with slight variations in the values of the complementarity indices. For example, the minimum value of the total variation complementarity index, Φ, is 0.190 in Dursey Sound, while the maximum value is 0.271 on the North-East Coast. Similar variations can be observed for metrics Φ_s and $\hat{\Phi}$. However, it is worth

TABLE I
COMPLEMENTARITY INDICES FOR ALL RAW RESOURCES AT SELECTED LOCATIONS AROUND IRELAND

Locations	Φ	Φ_s	$\hat{\Phi}$
Inishtrahull Sound	0.270	0.500	0.569
NorthEast Coast	0.271	0.499	0.570
Copeland Islands	0.257	0.439	0.528
Codling Arklow Banks	0.258	0.463	0.522
Carnsore Point	0.253	0.465	0.534
Gascanane Sound	0.231	0.467	0.555
Dursey Sound	0.190	0.464	0.556
Strangford Lough	0.239	0.431	0.563
Lough Foyle	0.206	0.464	0.563
Shannon Estuary	0.247	0.438	0.526
Bulls Mouth	0.222	0.477	0.549

noting that the metrics based on standard deviation and variance, i.e. Φ_s and $\hat{\Phi}$, tend to overestimate the complementarity, which align with the results obtained using similar metrics in [12]. Among the two, $\hat{\Phi}$ yields the highest values, primarily due to the re-scaling process in Eq. (6).

Fig. 6 depicts the comparative analysis of the three metrics on a seasonal timescale. In this case, the data from all locations are combined to highlight the seasonal complementarity. Once again, Φ exhibits a consistent pattern with small variations ranging from 0.33 to 0.37, demonstrating the highest complementarity during the summer season. Conversely, Φ_s and $\hat{\Phi}$ display significantly greater variations compared to Φ, with the lowest values observed in winter and higher values in spring and summer seasons. The larger variations in Φ_s and $\hat{\Phi}$ can be attributed to the nature of solar resource during the winter season, where its availability is substantially lower, resulting in greater sensitivity to data variations for these metrics.

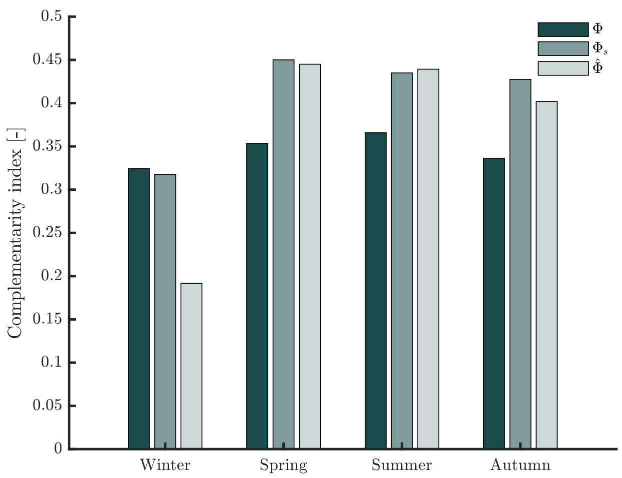

Fig. 6. Seasonal complementarity among four resources around Ireland, considering all chosen data points in Fig. 2.

To demonstrate the impact of different resource combinations in the resource mix on the complementarity indices, Table II provides the complementarity indices for various resource mix configurations for the Island of Ireland. Table II clearly illustrates that increased diversity in the resource mix corresponds to higher levels of complementarity. Specifically, considering Φ as a metric, it is evident that complementarity is lower for resource mixes comprising only two resources, and it progressively increases with the addition of a third resource. Thus, the addition of marine energy sources, i.e. wave and tidal, to the wind-solar mix increases overall complementarity. The highest complementarity is achieved when all four resources are included, as shown by the highlighted row in green in Table II. Again, it can be noted that Φ_s and $\hat{\Phi}$ not only tend to overestimate the complementarity for different resource mixes, but they also exhibit greater sensitivity to the addition of new resources in the mix.

TABLE II
COMPLEMENTARITY INDICES FOR VARIOUS COMBINATIONS OF RESOURCE-MIX FOR ISLAND OF IRELAND.

Resource Mix	Φ	Φ_s	$\hat{\Phi}$
Wave-wind	0.1055	0.0776	0.1920
Wave-tidal	0.0755	0.3135	0.5347
Wave-solar	0.0753	0.3632	0.6031
Wind-tidal	0.1930	0.2617	0.5101
Wind-solar	0.2232	0.3567	0.5891
Tidal-solar	0.1890	0.2689	0.4985
Wave-wind-tidal	0.2647	0.0417	0.2597
Wave-wind-solar	0.2647	0.0420	0.4223
Wind-tidal-solar	0.3217	0.1478	0.5835
Wave-wind-tidal-solar	0.3470	0.4554	0.4447

The findings presented in this paper highlight several potential benefits that can arise from introducing more diversity into the electricity generation mix in Ireland. The inclusion of marine energy sources, specifically wave and tidal energy, has been shown to enhance the availability and continuity of renewable generation profiles by effectively complementing wind and solar energy generation. Furthermore, diversifying the supply systems through the integration of marine energy can potentially reduce the need for extensive energy storage to mitigate the temporal variabilities associated with renewable energy sources. The increased complementarity among different renewable resources can contribute to a more balanced and consistent electricity supply, thereby minimising the requirements for large-scale energy storage solutions. However, a comprehensive quantitative analysis is necessary to substantiate these claims, and such analysis falls beyond the scope of the present study. Further research is required to delve deeper into the quantification of these potential benefits and their implications for the overall energy system in Ireland.

Furthermore, the findings of this study highlight another important aspect related to complementarity quantification, which has traditionally been approached through the lens of *negative correlation* in the existing literature [2], [12], [13]. Using a total variation-based index, Φ, allows for consistent complementarity assessment by considering the regularity measure of the sum of the variables as a fundamental concept in evaluating complementarity. On the other hand, standard deviation and variance-based metrics, i.e. Φ_s and $\hat{\Phi}$, have been shown to be more sensitive to variations, and tend to overestimate complementarity.

V. Conclusions

In this paper, we present a complementarity assessment of four renewable energy resources, i.e. wave, wind, tidal, and solar, around the Island of Ireland. The assessment is carried out using three complementarity indices: Φ, Φ_s, and $\hat{\Phi}$, which allow for the evaluation of complementarity among more than two resources simultaneously. The results reveal consistent trends across the three metrics for various test conditions. However, the total variation complementarity index Φ provides reliable and consistent results, compared to the metrics Φ_s and $\hat{\Phi}$, which tend to overestimate complementarity and exhibit higher sensitivity to variations in the time-series data. The results also highlight the positive relationship between complementarity and the diversity of supply systems, suggesting that adding marine energy resources (wave and tidal) to the wind-solar mix potentially benefits the Irish energy supply in terms of reduced storage and reserve requirements.

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