Implications of Solar–Wind Resource Complementarity for Hybrid Renewable Systems in Northern Islands, Sri Lanka

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Abstract: Islanded and remote power systems in Sri Lanka's Northern region faces challenges in maintaining reliable electricity supply while transitioning toward higher shares of renewable energy. Solar Photovoltaic (PV) and wind resources represent promising alternatives; however, their inherent intermittency require careful evaluation of resource complementarity to enhance system stability and reduce storage dependency. This study investigates the temporal complementarity between solar and wind resources in selected Northern islands of Sri Lanka using hourly generation data. Three complementary assessment metrics are employed: the Pearson correlation coefficient (r), the Complementarity Index (CI), and Cross-Correlation Function (CCF) analysis. The analysis is conducted at annual and seasonal scales where the latter further divided into four monsoon periods to capture climatic influences specific to the region. Results indicate weak to moderate negative correlation during key monsoon periods, suggesting beneficial complementarity between the two resources. The Complementarity Index further confirms seasonal smoothing effects, while cross-correlation analysis reveals time-lag interactions that can be exploited for improved hybrid system scheduling. The findings demonstrate that integrating solar PV and wind generation can significantly enhance supply reliability for islanded systems in Northern Sri Lanka. The study provides quantitative insights to support optimal hybrid system planning and future renewable energy deployment strategies in monsoon-dominated regions.

Keywords: hybrid renewable energy systems, island electrification, resource complementarity, solar energy, wind energy

1. Introduction

1.1. Background

Sri Lanka has set an ambitious target of achieving 70% renewable energy capacity by 2030. In line with this goal, the country is actively expanding the utilization of renewable energy resources to meet future electricity demand [1]. Due to its favorable geographical location, Sri Lanka has significant potential for both solar Photovoltaic (PV) and wind energy development.

In recent years, solar energy development has grown rapidly through small scale rooftop solar PV installations and large-scale ground-mounted solar PV plants. This expansion has contributed positively to the renewable energy share of the grid. However, the existing power system infrastructure is struggling to accommodate the increasing solar penetration. During periods of high solar generation and low electricity demand, the grid experiences operational challenges leading to the grid instability and occasional blackouts.

While solar energy offers clear environmental and economic benefits, it is inherently intermittent. Solar power generation is restricted to daytime hours and is highly influenced by weather conditions such as cloud cover [2]. As a result, maintaining a continuous and reliable power supply using solar energy alone becomes challenging. Although energy storage systems can help mitigate this issue, their high cost and technical requirements currently limit widespread adoption.

To address the limitations of single renewable resources, hybrid energy systems have gained increasing attention. Particularly, integrating solar and wind energy can reduce overall power variability, as wind resources are often available during nighttime or periods of low solar output [3]. This complementary behavior enables more effective utilization of local renewable resources. Consequently, solar–wind hybrid systems are especially suitable for rural areas and weak power grids, where improving supply reliability and energy security is critical.

1.2. Motivation

The northern islands of Sri Lanka present a good potential for hybrid renewable energy development. These areas experience strong wind conditions alongside adequate solar potential throughout the year [4]. The islands are inhabited by small communities with distinct cultural identities. All these islands remain disconnected from the national grid and electricity supply is operated by the Ceylon Electricity Board (CEB) through isolated power systems. Several completed and ongoing hybrid renewable energy projects in these regions are primarily designed using annual average resource assessments, which may not fully capture temporal variations [4].

Due to the absence of grid connectivity, electricity generation in these islands relies heavily on diesel generators. This dependence results in high electricity generation costs, largely because fuel must be transported by sea under challenging conditions [4]. Furthermore, reliance on diesel raises concerns related to fuel supply reliability, operational sustainability, and environmental impact. These challenges highlight the need for sustainable alternatives that can reduce diesel consumption while maintaining reliable power supply.

Although renewable energy potential in these regions is well recognized, most existing studies focus on monthly or annual mean values of solar radiation and wind speed [5]. Such approaches provide limited insight into the temporal interaction between solar and wind resources. In particular, there are very few studies that apply quantitative complementarity metrics to assess how these resources interact over time, which creates uncertainty in hybrid system planning and design [6].

1.3. Research Gap

Despite the high availability of solar and wind resources, the temporal complementarity between them in Sri Lanka's northern islands has not been systematically analyzed. Local climatic characteristics, including monsoon-driven wind patterns and cloud-induced solar variability, play a significant role in resource behavior but are rarely incorporated into detailed complementarity assessments. This lack of region-specific analysis limits the ability to accurately evaluate the performance and reliability of solar–wind hybrid systems.

1.4. Aims & Objectives

This study aims to provide a detailed assessment of solar-wind complementarity in Sri Lanka's northern islands. The specific objectives are:

- To examine the temporal characteristics of solar and wind energy resources, including diurnal, seasonal, and monthly variations, in order to properly understand their availability and intermittency.
- To quantitatively evaluate the degree of complementarity between solar and wind resources using

statistical indicators such as the Pearson correlation coefficient (*r*), the Complementarity Index (CI), and Cross-Correlation Analysis (CCF).

- To assess the implications of solar-wind complementarity for hybrid system reliability, particularly in terms of reducing power fluctuations and improving the continuity and stability of electricity supply.

2. Study Area and Data

2.1. Study Area

There are several small islands located in the northern region of Sri Lanka, among which Delft Island was selected as the study area. Delft Island is situated in the Palk Strait off the Jaffna Peninsula at approximately latitude 9°52’ N and longitude 79°67’ E, as illustrated in Fig. 1. It has a land area of about 50 km^2, making it the largest inhabited island in the northern island group. The island is roughly flat and oval-shaped and is surrounded by shallow waters with coral-lined beaches [7]. Delft is also the farthest island from the mainland, located at a distance of approximately 10 km from the Jaffna Peninsula.

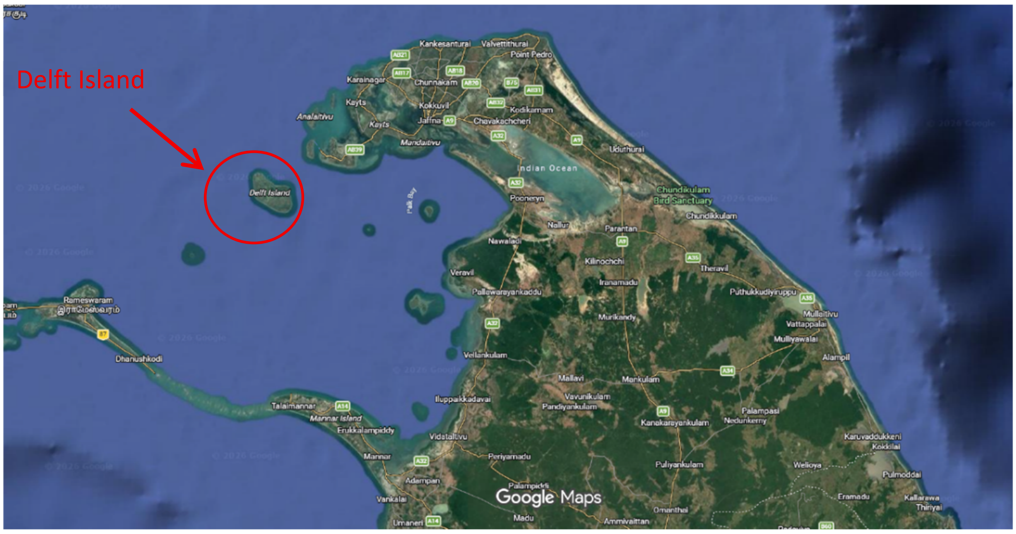

Fig. 1. Geographic location of Delft Island.

Delft Island lies within a semi-arid climatic zone, receiving an average annual rainfall of approximately 750 mm. Generally, the island experiences four distinct seasonal variations: the Southwest Monsoon (SWM) from May to September, the Northeast Monsoon (NEM) from December to February, and two inter monsoons namely, the First Inter-Monsoon (FIM) from March to April and the Second Inter-Monsoon (SIM) from October to November [8]. The rainfall is influenced by the monsoon patterns, primarily occurs from October to February, while extended dry periods are observed from May to September. Despite the seasonal rainfall, many days remain clear and sunny throughout the year [7]. The island is also exposed to strong and persistent wind conditions, largely influenced by monsoon circulation. The coexistence of high solar irradiation and monsoon driven wind regimes makes Delft Island a suitable location for assessing the potential of hybrid solar–wind energy systems.

The island has an estimated population of around 4,540 people, comprising approximately 1,430 families. The local economy is primarily based on fishing and palmyra cultivation, which are the main livelihood activities of the community. The electrification level of the island is about 87%, and electricity consumption is dominated by household demand. The average daily energy requirement is approximately 2,780 kWh, with the system peak demand occurring during nighttime hours and reaching around 211 kW [4].

Delft Island was selected for this study because it is the largest, most distant, and highest-demand island among the northern island group. In addition, the cost of electricity generation on the island is relatively high compared to other islands due to its reliance on isolated power systems. Therefore, a careful assessment of solar and wind resource availability and their temporal complementarity is essential to support improved hybrid renewable energy planning and to reduce overall energy generation costs.

2.2. Data Description

Hourly meteorological data for the selected island were collected from the NASA Power Data Access Viewer database, which provides satellite-based and reanalysis-derived data and is widely used in renewable energy studies, particularly in regions with limited ground-based measurements [9]. The data were obtained for a one-year study period from January to December, with a temporal resolution of one hour, enabling detailed analysis of short-term and seasonal resource variations.

The dataset includes the following key variables:

- Solar irradiance, represented by all-sky surface shortwave downward irradiance (Global horizontal irradiance)
- Wind speed measured at a height of 10 m above ground level
- Ambient air temperature measured at a height of 2 m.

These variables were selected because they directly influence photovoltaic and wind power generation and are commonly used in renewable energy resource assessment studies. The collected data form the basis for estimating solar and wind power output and for conducting the subsequent complementarity analysis.

2.3. Data Pre-processing

2.3.1 PV power modelling

Solar irradiance data were converted into Photovoltaic (PV) power output using a simplified PV performance model. The model considers the influence of both solar irradiance and ambient temperature on PV module performance [2]. The PV power output was estimated using the following expression:

$$P_{PV} = \eta SI(1 + \gamma(t_0 - 25)) \tag{1}$$

where P_{PV} is the PV power output, η represents the overall PV conversion efficiency (%), S is the total area (m^2), I is the solar irradiance ($\mathrm{W/m^2}$), γ is the temperature coefficient of power ($°\mathrm{C}^{-1}$), t_0 denotes the ambient air temperature ($°\mathrm{C}$). The reference temperature of $25\,°\mathrm{C}$ corresponds to Standard Test Conditions (STC).

In this study, $600\,\mathrm{Wp}$ monocrystalline PV modules are considered targeting an approximate 300 MW plant capacity, representing typical utility-scale installation. The PV conversion efficiency (η) is assumed to be 21%, while the total installation area (S) is taken as $3{,}000\,\mathrm{m}^2$. To account for temperature effects, a temperature coefficient (γ) of $-0.0036\,°\mathrm{C}^{-1}$ is used, reflecting the reduction in module efficiency with increasing temperature. This is particularly relevant under the warm climatic conditions of the study area, where the average ambient temperature is greater than the STC temperature.

2.3.2 Wind power modelling

Wind speed data obtained at a reference height of $10\ \mathrm{m}$ were first extrapolated to the wind turbine hub height using the following standard power-law profile [10].

$$V_h = V_{10}\left(\frac{h}{10}\right)^{\propto} \tag{2}$$

where V_h is the wind speed at hub height $h(\mathrm{m/s})$, V_{10} is the wind speed at $10\ \mathrm{m}$ height $(\mathrm{m/s})$, and α is the wind shear exponent, which accounts for the wind speed variation with height, is assumed to be 0.12, reflecting the relatively low surface roughness characteristics of the coastal terrain of Delft Island.

In this study, mid-scale wind turbines with a hub height (h) of $30\ \mathrm{m}$ and a rotor diameter (D) of $15\ \mathrm{m}$ are considered. Each turbine is rated at $60\ \mathrm{kW}$, and a total of five units are assumed, resulting in an overall installed capacity of $300\ \mathrm{kW}$.

The extrapolated wind speed was then converted into wind power output using a simplified wind power model based on the turbine power curve characteristics. To this study, wind power output was estimated assuming an idealized turbine response within the cut-in and rated wind speed range [10].

$$P_{Wind} = \eta C_P(\frac{1}{2}\rho A\, V_h^3) \tag{3}$$

where P_{Wind} is the wind power output (W), ρ is the air density $(\mathrm{kg/m^3})$, A is the rotor swept area $(\mathrm{m^2})$, C_P is the power coefficient of the wind turbine, and V_h is the wind speed at hub height $(\mathrm{m/s})$.

The resulted swept area (A) was approximately $176.7\ \mathrm{m^2}$. The air density (ρ) is assumed at a standard sea-level value of $1.225\ \mathrm{kg/m^3}$. The aerodynamic performance of the turbine is defined by a power coefficient (C_P) of 0.4, while the overall mechanical and electrical conversion efficiency (η) is assumed to be 85% to account for generator losses.

2.3.3 Capacity factor normalization

In order to compare the behaviour of solar and wind resources on a common basis, Capacity Factor (CF) was used in this study. Capacity factor indicates how much energy a system produces relative to its maximum possible output and is widely used to describe the availability of renewable energy resources over time [11]. By using capacity factors instead of absolute power values, the analysis focuses on the temporal variation of the resources rather than the installed system size.

The capacity factor for both solar and wind power was calculated using the following general expression:

$$CF = \frac{P(t)}{P_{rated}} \tag{4}$$

where $P(t)$ is the estimated power output at a given hour and P_{rated} is the rated capacity of the corresponding energy system which is assumed to be 300 kW for both solar PV and wind systems in this study.

The capacity factors were calculated at an hourly time resolution and take values between 0 and 1. These normalized time series were then used in the subsequent correlation, complementarity index, and cross-correlation analyses to evaluate how solar and wind resources complement each other over different time scales.

3. Methodology

3.1. Descriptive Analysis

Descriptive analysis was carried out as the first step of the study to examine the temporal behavior and variability of solar and wind energy resources prior to applying quantitative complementarity metrics.

To capture resource characteristics across different time scales, three levels of descriptive analysis were performed: annual diurnal profiles, monthly average profiles, and seasonal diurnal profiles.

3.1.1. Annual diurnal profiles

Annual diurnal profiles were developed to represent the typical daily generation pattern of solar and wind resources over the entire study period. For this purpose, hourly capacity factor values corresponding to the same hour of the day for 24 hours were averaged across all 365 days.

This approach smooths short-term fluctuations and highlights systematic daily trends, allowing direct comparison of daytime solar generation with wind generation behavior during both daytime and nighttime hours.

3.1.2. Monthly average profiles

Monthly average profiles were constructed to assess medium term temporal variations in solar and wind generation throughout the year. Hourly capacity factor data were grouped by month, and average monthly capacity factors were computed separately for solar and wind.

This analysis captures the influence of changing solar angles, cloud cover, and monsoon-driven wind regimes on resource availability. Monthly profiles are particularly useful for identifying seasonal trends and assessing the consistency of each resource across different periods of the year.

3.1.3. Seasonal diurnal profiles

To further investigate climate-driven effects, seasonal diurnal profiles were generated based on monsoon classification mentioned Section 2. The hourly dataset was grouped into the four seasonal periods as NEM, FIM, SWM, SIM [8].

For each season, diurnal profiles were created by averaging hourly power generation across all days belonging to the respective season. This enables evaluation of how daily solar and wind generation patterns vary under different seasonal wind and cloud conditions, and how seasonal complementarities may differ from annual averages.

3.2. Complementarity Metrics

To quantitatively assess the degree of complementarity between solar and wind energy resources, three complementary statistical indicators were employed: the Pearson correlation coefficient (r), the Complementarity Index (CI), and Cross-Correlation Analysis (CCF). These metrics were selected to capture different aspects of resource interaction, including simultaneous variability, variability smoothing potential, and time-lagged relationships.

All complementarity analyses were performed using hourly capacity factor time series for solar and wind power.

3.2.1. Correlation Coefficient (r)

The Pearson correlation coefficient was used to assess the linear relationship between solar and wind generation profiles. It quantifies the extent to which variations in solar and wind capacity factors occur simultaneously over time [12].

The correlation coefficient is defined as [13]:

$$r = \frac{\sum_{t=1}^{N}(CF_{PV,t}-\bar{CF}_{PV})(CF_{Wind,t}-\bar{CF}_{Wind})}{\sqrt{\sum_{t=1}^{N}(CF_{PV,t}-\bar{CF}_{PV})^2}\sqrt{\sum_{t=1}^{N}(CF_{Wind,t}-\bar{CF}_{Wind})^2}} \tag{5}$$

where $CF_{PV,t}$ and $CF_{Wind,t}$ represent the hourly capacity factors of solar and wind generation at time step t, $\bar{CF}_{PV}$ and $\bar{CF}_{Wind}$ denote their respective mean values, and N is the total number of hourly observations where $N = 8760$ for annual analysis.

The application of this metric assumes a linear relationship between the variables and an approximately normal distribution of the data, which is generally acceptable for large-scale atmospheric datasets. Negative correlation values indicate inverse behavior between solar and wind generation, while values close to zero suggest weak or independent temporal relationships. By evaluating r at multiple temporal scales, including annual, seasonal, monthly and hourly scales, the analysis captures both short-term and long-term variability in resource interaction under different climatic conditions.

3.2.2. Complementarity Index (CI)

To further evaluate the potential of solar and wind resources to reduce overall generation variability when combined, the Complementarity Index (CI) was employed. Unlike correlation coefficients, the CI focuses on the variability smoothing effect achieved through resource combination.

The Complementarity Index is defined as [14]:

$$CI = 1 - \frac{\sigma_{PV+Wind}}{\sigma_{PV}+\sigma_{Wind}} \tag{6}$$

where σ_{PV} and σ_{Wind} are the standard deviations of solar and wind capacity factors, respectively, and $\sigma_{PV+Wind}$ is the standard deviation of the combined solar wind generation.

The use of CI assumes that a reduction in total variance reflects improved system reliability. The index was evaluated at both annual and seasonal scales to assess how complementarity varies under different climatic and monsoonal conditions. CI value close to 1 indicates strong complementarity, where variations in one resource are balanced by the other, resulting in a smoother combined output. In contrast, a CI near 0 suggests that both resources vary in a similar manner. To ensure consistency, both resources are normalized to the same rated capacity (300 kW), allowing direct comparison of variability.

3.2.3. Cross-Correlation Analysis

Cross-correlation analysis was conducted to investigate time-lagged relationships between solar and wind generation profiles. This method enables identification of whether variations in one resource tend to precede or follow changes in the other, which is particularly relevant for understanding diurnal and monsoon-driven complementarities.

The cross-correlation function is expressed as [9]:

$$CCF(\tau) = \frac{\sum_{t=1}^{N-\tau}(CF_{PV,t}-\bar{CF}_{PV})(CF_{Wind,t+\tau}-\bar{CF}_{Wind})}{\sqrt{\sum_{t=1}^{N}(CF_{PV,t}-\bar{CF}_{PV})^2}\sqrt{\sum_{t=1}^{N}(CF_{Wind,t}-\bar{CF}_{Wind})^2}} \tag{7}$$

where τ represents the time lag in hours. Positive lag values indicate wind generation lagging solar generation, while negative lag values indicate wind generation leading solar generation.

In this study, cross-correlation was evaluated over a ±12-hour lag window to capture the diurnal variation in solar and wind patterns, which are mainly impacted by heating–cooling cycles. The magnitude and sign of the cross-correlation coefficients provide insight into the strength and direction of time-shifted interactions between solar and wind resources.

This analysis is important for hybrid system design, as it identifies how long Energy Storage Systems (ESS) are required to supply power. It assumes that hourly capacity factor data is consistent across time shifts and significant peaks within the CCF are interpreted as recurring patterns, which provide a reliable basis for optimizing microgrid operations.

4. Results and Discussion

4.1. Descriptive Statistics

The temporal characteristics of solar and wind energy resources at the selected island were examined using hourly data over a one year period. Table 1 summarizes the key descriptive statistics of the main variables considered in this study.

Table 1. Descriptive Statistics of Solar and Wind Energy Related Variables

Variable	Mean	Std. Dev.	Min	Max
Ambient Temperature (°C)	28.97	1.57	24.57	33.30
PV Power (kW)	143.93	195.69	0.00	658.17
Wind Speed (m/s)	6.80	2.63	0.13	16.04
Wind Power (kW)	98.47	94.63	0.00	894.15
PV Capacity Factor	0.35	0.43	0.00	1.00
Wind Capacity Factor	0.32	0.28	0.00	1.00

The mean ambient temperature of approximately 28.97 °C indicates a consistently warm climate, which is favorable for solar energy generation throughout the year. Solar PV power exhibits a high standard deviation relative to its mean, reflecting strong diurnal variability and the absence of generation during nighttime hours. In contrast, wind power shows comparatively lower variability, with non-zero generation occurring during both day and night. This difference in temporal behavior highlights the potential for wind energy to partially compensate for periods of low or zero solar output.

The capacity factor statistics further emphasize this contrast. While both solar and wind show similar annual mean capacity factors, solar capacity factors span a wider range, indicating sharper fluctuations. Wind capacity factors are more evenly distributed, suggesting more stable generation over time.

4.2. Diurnal, Seasonal and Monthly Characteristics

The analysis focuses on diurnal, seasonal, and monthly variations in order to capture the inherent intermittency of each resource and to understand their availability patterns across different time scales.

Fig. 2 illustrates the average diurnal profiles of solar and wind power generation. While solar PV generation follows the expected pattern, the wind power shows a relatively smoother diurnal profile and maintains considerable generation during night-time periods. A key trend that can be observed is the slight dip in wind capacity factor approximately between 10 am–03 pm, which coincides with solar peak. This inverse behavior is a classic signature of coastal regions, where the thermal gradient between the land and the Palk Strait shifts. This behavior is particularly important for isolated island systems, where wind generation ramp up with solar generation ramp down, specifically addressing the evening demand peak.

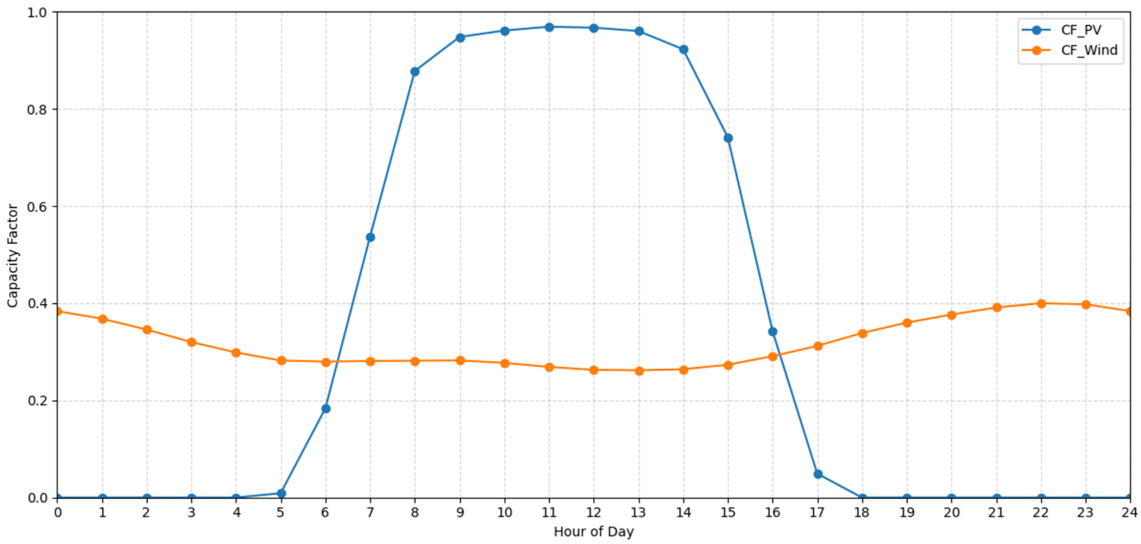

Fig. 2. Diurnal profile of solar & wind generation.

Seasonal diurnal profiles, shown in Fig. 3, reveal the influence of monsoon-driven wind regimes on wind power availability. During the Southwest Monsoon (SWM), wind generation reaches its highest levels, while solar output shows higher variability compared to the First Inter-Monsoon (FIM). This is attributed to the intermittent cloud cover associated with monsoon fronts. Higher solar PV generation is observed during the inter-monsoon months of March and April, resulting in increased solar irradiance as the sun's path becomes nearly overhead to the island during this period.

The seasonal persistence of solar generation, combined with wind intensity during monsoon periods, enhances the overall reliability of a hybrid solar wind system. These results suggest that seasonal complementarity can help smooth power output over longer time scales.

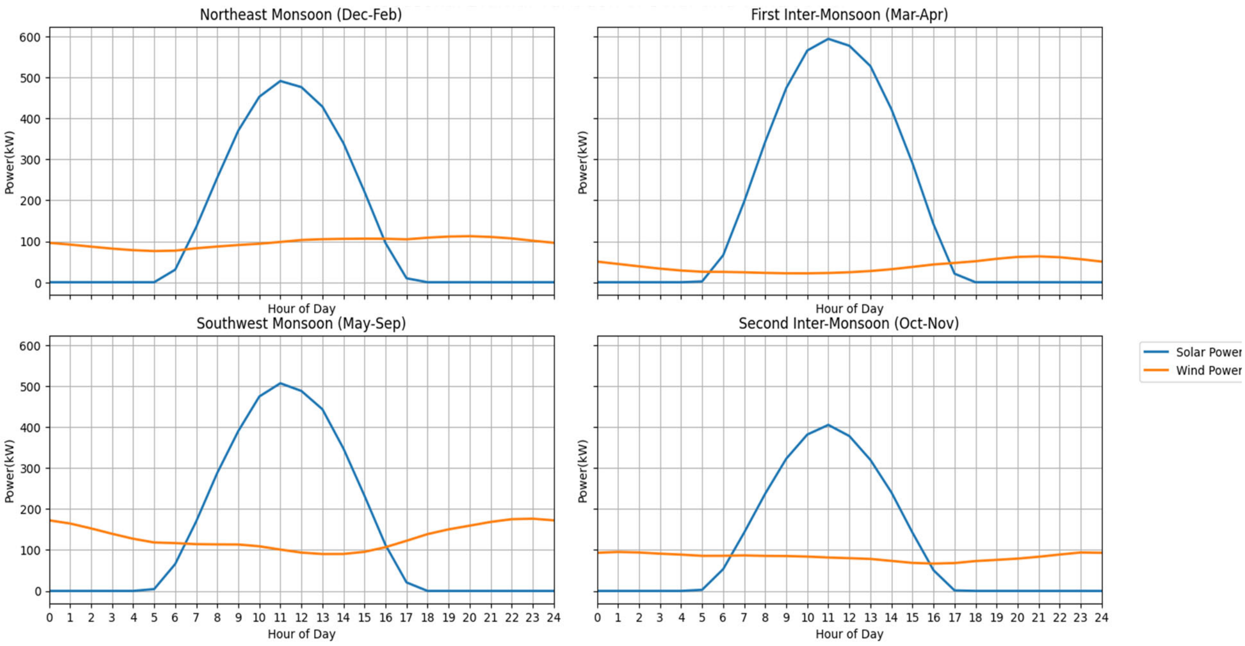

Fig. 3. Seasonal diurnal variation of solar & wind power.

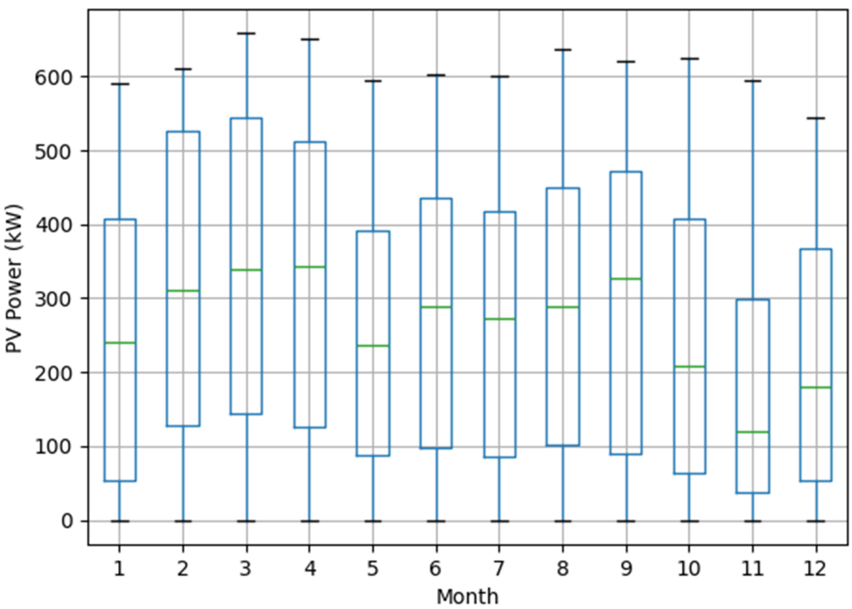

Fig. 4. Monthly PV power generation (daylight hours).

Figs. 4 and 5 present the monthly average generation patterns of solar and wind power. Solar output in Fig. 4 shows relatively minor month-to-month variation, reflecting the island's proximity to the equator and consistent solar irradiation throughout the year. However, Fig. 5 shows a clear seasonal drop in wind generation during the second inter-monsoon months, where it reaches its lowest levels. This creates a temporary gap in energy supply within the hybrid system. The results indicate that solar provides a relatively stable daily energy supply, while wind varies more across seasons and acts as a supporting source. This difference highlights the need for the Complementarity Index (CI), to evaluate whether these variations help reduce long-term storage requirements.

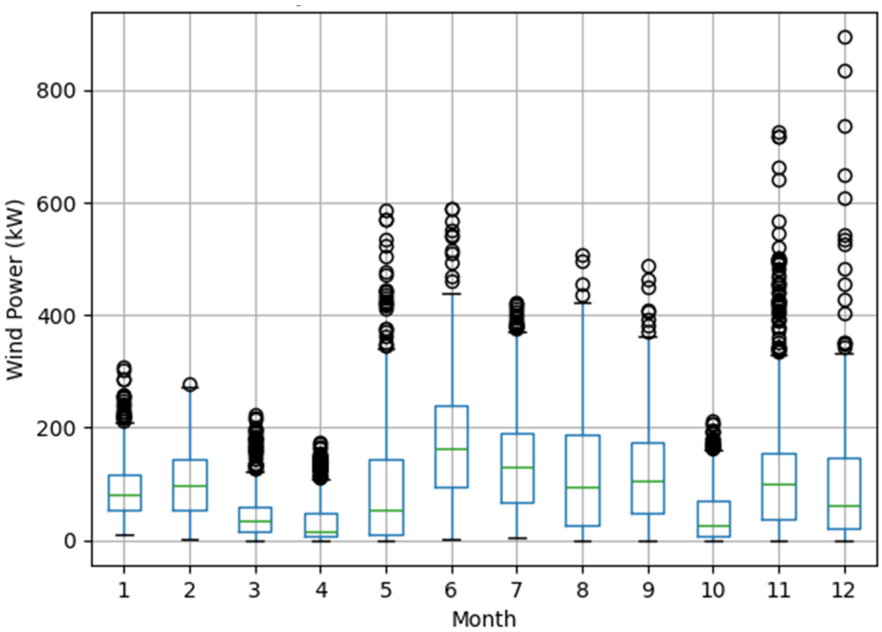

Fig. 5. Monthly wind power generation (24 h).

4.3. Correlation Analysis Results

The degree of complementarity between solar and wind energy resources was evaluated using the Pearson correlation coefficient, the Complementarity Index (CI), and cross-correlation analysis based on hourly capacity factor time series.

The annual Pearson correlation coefficient between solar and wind generation was -0.1612, indicating a weak negative correlation. The statistical significance of this relationship was confirmed by a p-value of $p < 0.001$, which is given by the large sample size ($N = 8760$) indicating the observed correlation is statistically robust. This suggests a modest natural balancing effect, where higher solar generation tends to coincide with slightly lower wind generation and vice versa. Although the correlation strength is low, the negative sign is favorable for hybrid system operation as it contributes to reduced overall variability.

Monthly correlation analysis shown in Fig. 6 further revealed that the relationship between solar and wind generation varies throughout the year, reflecting seasonal changes in solar availability and monsoon driven wind patterns. A significant trend is observed during the Southwest Monsoon (June to August), where the correlation becomes more negative. This indicates that wind generation tends to increase when solar output decreases, helping to balance the system during cloudy or evening periods. In contrast, during the inter-monsoon months (such as April and October), the correlation moves closer to zero or slightly positive. This reflects weaker wind conditions along with stable and high solar generation. These results highlight an important seasonal limitation. For a microgrid on Delft Island, this implies that while the resources are generally well balanced for most of the year, the inter-monsoon months may require greater support from energy storage or backup generation to maintain stable operation.

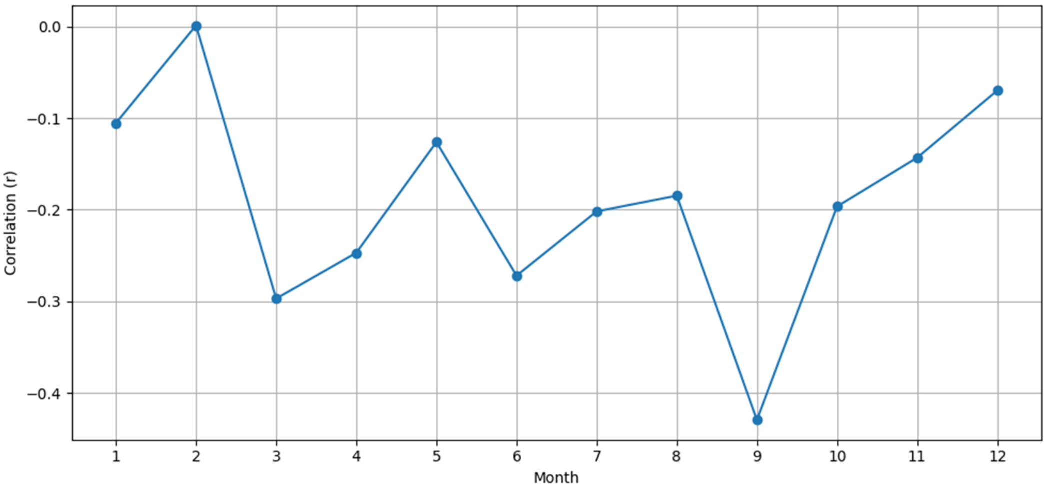

Fig. 6. Monthly solar-wind complementarity.

4.4. Complementarity Index Results

The annual Complementarity Index (CI) was calculated as 0.331, confirming a moderate level of complementarity between solar and wind resources at the study location. This value indicates that combining solar and wind generation has the potential to reduce overall power variability compared to single-resource operation.

Seasonal CI values reveal notable variations in complementarity across different monsoon periods, as shown in Table 2. The lowest CI was observed during the FIM season, while higher complementarity was observed during the SIM and SWM seasons. These seasonal differences highlight the influence of monsoon driven wind patterns and changing solar availability on hybrid system performance.

Table 2. Seasonal CI Values

Season	CI
FIM	0.248496
NEM	0.274905
SIM	0.361078
SWM	0.348118

4.5. Cross-Correlation Results

The cross-correlation analysis, illustrated in Fig. 6, provides a temporal dimension to the resource interaction. The strongest cross-correlation value of −0.162 was observed at a lag of −23 h, indicating that wind generation tends to increase nearly one day before periods of higher solar generation. Although the magnitude of the correlation is relatively low, its timing is highly significant. A peak close to the 24-hour lag indicates a consistent daily shift between solar and wind generation. This suggests that wind speeds tend to increase in a regular cycle, likely due to evening land–sea temperature differences, and occur at a different time than peak solar output. This predictable pattern shows that wind and solar are not random, but follow a daily cycle that can support each other. In a hybrid microgrid, this time difference helps smooth the total power output, as wind generation often increases when solar decreases, reducing the reliance on Energy Storage Systems (ESS). Overall, while the complementarity is less strong, it is meaningful and can help reduce dependence on diesel backup in island systems. Although the magnitude of the correlation is weak, this result suggests a temporal offset between the two resources, which can contribute to smoothing power supply when both are integrated into a hybrid system.

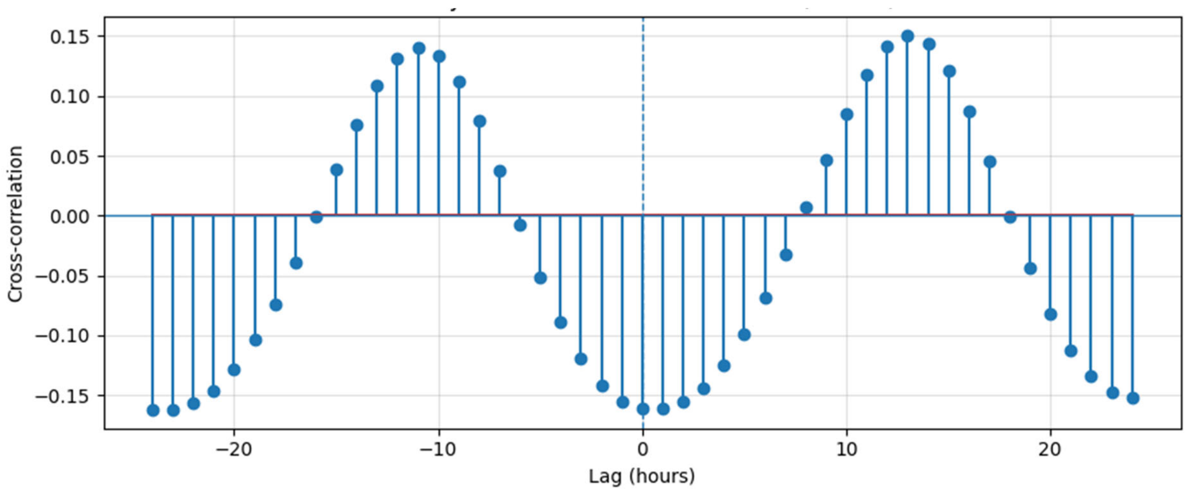

Fig. 6. Hourly solar-wind cross-correlation (annual).

5. Implications for Hybrid Renewable Systems

The observed temporal complementarity between solar and wind resources has important implications for the design and operation of hybrid renewable energy systems, particularly in isolated island contexts such as Sri Lanka's northern islands.

From an operational perspective, the weak negative correlation and moderate complementarity index values indicate that solar and wind generation can partially balance each other over time. Periods of low solar output, especially during night time or cloudy conditions, often coincide with relatively higher wind availability, reducing short-term power fluctuations. This natural smoothing effect can improve supply reliability and reduce operational stress on isolated power systems.

In terms of system planning, the results suggest that hybrid solar–wind configurations can achieve improved performance compared to single-resource systems, even without large energy storage capacities. The observed complementarity indicates that appropriately designed hybrid systems may reduce reliance on oversized storage or excessive backup generation. This is particularly relevant for island microgrids where space, cost, and maintenance constraints limit large-scale storage deployment.

The findings also have practical implications for reducing diesel dependency in isolated power systems. By leveraging complementary solar and wind profiles, hybrid systems can decrease the operating hours of diesel generators, leading to lower fuel consumption, reduced emissions, and improved energy security. This is especially important for island electrification projects where fuel transportation is costly and logistically challenging.

From a policy perspective, the results support the promotion of hybrid renewable microgrids as a viable strategy for island electrification in Sri Lanka. Incorporating complementarity-based assessments into planning frameworks can lead to more reliable and cost-effective renewable energy projects, supporting national renewable energy targets while improving resilience in remote communities.

6. Conclusion

This study investigated the temporal characteristics and complementarity of solar and wind energy resources for a selected northern island in Sri Lanka using hourly data over a one-year period. Diurnal, seasonal, and monthly analyses were conducted to capture the variability and availability patterns of each resource.

The complementarity between solar and wind generation was quantified using the Pearson correlation coefficient, complementarity index, and cross-correlation analysis. The results indicate a weak negative annual correlation and moderate complementarity, with noticeable seasonal and monthly variations influenced by monsoon-driven wind regimes and solar availability. These findings highlight the potential of solar–wind hybrid systems to improve power supply stability in isolated island grids.

Methodologically, the study demonstrates the value of combining multiple complementarity metrics to capture both simultaneous and time-lagged interactions between renewable resources. Practically, the results provide useful insights for hybrid system planning, particularly in regions where renewable resources are abundant but grid infrastructure is weak or isolated.

This analysis is based on a single year of data, which may not fully capture long-term climatic variability. Future research can extend this work by incorporating multi-year datasets to improve the robustness of the complementarity assessment. Integrating hybrid system sizing and optimization techniques would allow direct evaluation of system performance and cost implications. Additionally, the inclusion of energy storage modeling and diesel dispatch strategies would provide a more comprehensive assessment of hybrid microgrid operation for island electrification.

Conflict of Interest

The author declares no conflict of interest.

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