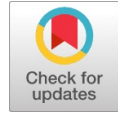


Characterizing Supply Reliability Through the Synergistic Integration of VRE towards Enhancing Electrification in Kenya

Denis Juma, Josiah Munda, Charles Kabiri



Abstract: Decentralized electrical power systems, driven by variable renewable energy sources such as solar PV and wind, have the potential to provide accessible and sustainable energy, contributing to the realization of a zero-carbon transition. However, these sources are susceptible to extreme weather conditions, presenting a challenge to the reliability of the power system. With abundant resources and a significant rural population lacking access to electricity, Africa has emerged as a key area for research on variable renewable energy-based electricity generation. Despite this focus, there remains a substantial gap in understanding at regional-scale the potential and variability of solar and wind power across various time scales, as well as the impact of available resource synergy. This study aims to bridge this knowledge gap by conducting comprehensive simulations of hybrid wind and solar energy systems, both on-grid and off-grid, across 20 geographically diverse locations in Kenya. Using high-resolution hourly time step data, we examine the effect of resource complementarity on system reliability at varying time scales: daily, monthly and annually. The study findings shows the available VRE resource exhibit moderate tendency for complementarity, and optimizing their deployment can reduce hourly variability by 20%, significantly enhancing supply reliability, especially in the northern and eastern regions.

Keywords: Variable Renewable Energy Sources, Complementarity, Adequacy, Reliability, Loss of Load Probability, Energy-mix Strategy

I. INTRODUCTION

Power networks are arguably one of humanity's most intricate and transformative ingenuity. It is impossible to overlook the fact that no nation has achieved economic industrialization without experiencing substantial increases in energy consumption. The foundations of basic services such as industries, schools, hospitals, and homes worldwide rely on electricity for daily operations. Consequently, the developing countries have recently witnessed a profound investments in power grids.

However, these investments have primarily concentrated on electricity access expansion, with little emphasis being placed on enhancing the quality of the electricity supplied through the existing infrastructure. Nevertheless, it is essential to acknowledge that poor reliability is often associated with decreased demand, utilization, and social benefits associated with electricity [1]. There is an encouraging shift underway in recognizing the significance of supply reliability. The Sustainable Development Goals of the United Nations now explicitly state that access to electricity should also be pegged on reliability [2]. Improving supply reliability can be more challenging to address than enhancing access. Enhancing supply reliability demands detailed information about the performance of various system attributes, from power generation all the way to the load centers. Historically, collecting this data has been costly and not a priority, especially with the present entry of Hybrid Renewable Energy Systems (HRES) in remote and far-flung areas [3]. And with a growing focus on renewable energy applications driven by technological advancements, environmental concerns, and the need for energy sustainability and security, this study aims to characterize the spatial supply reliability of such integrated renewable energy systems utilizing solar and wind power to mitigate their respective weaknesses and ensure a more reliable energy supply.

One of the key benefits of hybrid energy systems is that they can leverage on the complementarity variable renewable energy sources (VRES) to reduce output variability and improve reliability. Complementarity refers to the concept that various renewable energy sources can integrate to deliver a more dependable and consistent energy supply. This entails that when one source is underperforming, other sources can compensate for the shortfall, thus creating a more robust and resilient energy system. In many instances, wind resources tend to be stronger at night, while solar resources are stronger during the day. This illustrates that combining wind and solar resources has the potential to create a more viable hybrid energy system. Numerous scholars have dedicated themselves to this area of exploring the impact of complementarity on the reliability of hybrid energy systems.

Firstly, a study by Mahmoudi et al. ascertained that by embracing complementarity, hybrid energy systems can deliver a remarkable decrease of up to 24% in loss of load probability [4][42][43][44]. Findings from a simulation study conducted by Liu et al. reveal that complementarity has the potential to enhance the capacity factor of hybrid energy systems by up to 10% [5].

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Another study by Liu et al. focuses on the effect of complementarity on the reliability of hybrid photovoltaic (PV)/battery energy storage systems. It aims to address the load demand in Iran, which is more vulnerable to variability though it was demonstrated the loss of load probability can be reduced by up to 20% by harnessing the available resource complementarity [6].

In addition to complementarity, there are a number of other factors that can affect the reliability of hybrid energy systems, such as the size and capacity of the wind and solar energy systems, as well as the capacity of the energy storage system, and the load demand. However, complementarity is one of the most important factors to consider when designing hybrid energy systems with enhanced reliability capability. Resource complementarity has emerged as a focal point in academic research, with diverse studies exploring its potential for reducing energy storage needs, its impact on net load, and its response to climate variability. Abed et al. [7] examined the relationship between solar and wind resource complementarity towards meeting electricity demand. Hoicka and Rowlands [8] demonstrated how the complementarity of solar and wind resources holds great promise for incorporating renewable energy into Ontario's power grid. In Italy, Monforti et al. [9] employed a Monte Carlo approach to examine wind and solar resource complementarity. De Jong et al. [10] examined the relation between wind and solar energy, electrical demand, by leveraging Brazil's hydropower resources, suggesting benefits for water conservation. Park and Salkut [11] demonstrated how the complementarity attributes of wind and solar resources enhances system reliability.

Sankaran and others [12] studied long-term correlations as well as cross-correlations of wind speed and solar radiation within an island in the United State. Santos-Alamillos et al. [13] demonstrated the significant impact of spatiotemporal correlation that impacts aggregated electricity generation from wind and solar energy sources around the Iberian Peninsula. With a case study of Oklahoma, Osofsky [14] focused on exploring the synergy between wind and solar resources proposing a method for calculating wind and solar radiation complementarity index. He also demonstrated how resource complementarity can improve the energy supply system reliability. The study demonstrated the model's ability to effectively represent the spatial and seasonal variability of renewable energy sources in Oklahoma. This precision is critical for designing and operating renewable energy infrastructure across the region. Harrison-Atlas et al. [15] on the other hand investigated at a regional level to affirm whether complementarity is an indicator of value, employing price taker analysis to estimate the existing and predicted future value factor for hybrid systems. Couto and Estanqueiro [16] approached solar and wind resource complementarity meteorologically in central and northern Portugal, while Bett and Thornton [17] explored it climatologically in UK. Castro et al. [18] investigated the variability of a number of variable renewable energy injected into the Portuguese power grid, demonstrating a high seasonal synergy for solar and wind energy resources.

Puspitarini et al. [19] carried out a spatial complementarity analysis comparing generators exploiting solar irradiation, which resulted in complementary clusters throughout Eastern

Italy. Furthermore, other researchers have explored complementarity between various resources such as solar-hydro [20], hydro-offshore wind [21], hydro-onshore wind [22], solar/wind-hydrokinetic [23], and solar/wind-hydro [24], [25]. Risso et al. have put forward an adept method of using complementarity roses to evaluate the spatial complementarity between wind and hydropower energy sources [26]. The growing body of literature underscores the increasing scholarly interest in resource complementarity in recent years.

This study aims to explore the impact of spatiotemporal complementarity between wind and solar resources on their overall supply reliability. The goal is to evaluate the impact of the synergistic relationship between solar and wind influences the ability of a Hybrid Renewable Energy System (HRES) to effectively meet the power demands. The approach taken relies on capacity factors for wind and solar generation, as well as their complementary characteristics. The study investigates how complementarity indices, spanning various time scales, affect the system's capacity to meet the set demand.

The structure of the paper is as follows: Section 2 details the methodology, encompassing data, simulation configuration, and metrics used to evaluate system reliability. Section 3 presents the results and discussion, which explain the resource complementarity effects on system reliability. The study ends with Section 4, which summarizing the main results and gives suggestion for further study prospects.

II. FRAMEWORK DESCRIPTION, DATA AND ASSUMPTIONS

A. Data

The widely used MERRA-2 (Modern-Era Retrospective Analysis for Research and Applications) reanalysis data set to evaluate the complementarity of VRE has been chosen for this study. A detailed description of the used data in the study is tabulated in Table 1.

Table- I: Summary Description of the Data Utilized in the Study

	Description
Spatial domain	4.5° N - 4.5° S and 34° E - 42° E
Spatial resolution	0.625° × 0.625° (Longitude / Latitude)
Temporal resolution	hourly

To evaluate the complementarity of the power output of the considered VRES, Global Horizontal Irradiance (GHI) and wind speed was generated from the MERRA-2 reanalysis dataset. These data were then utilized to generate time series for solar PV and wind power. The method described in the preceding subsections was employed for this task.

B. System Configuration and Simulation

The concept of complementarity is typically examined with the context of smoothening the aggregated power generation [27], [28].

To effectively characterize the spatial supply reliability, complementarity is analyzed in this study with the objective of fully meeting the load demand; complementarity towards load matching.

Correlation analysis, which essentially involves comparing the degree of synchronization between any two

distinct time series, was adopted in this study.

Figure 1 summarizes the overall approach that was adopted to analyze how temporal complementarity affects the system supply reliability within the study area.

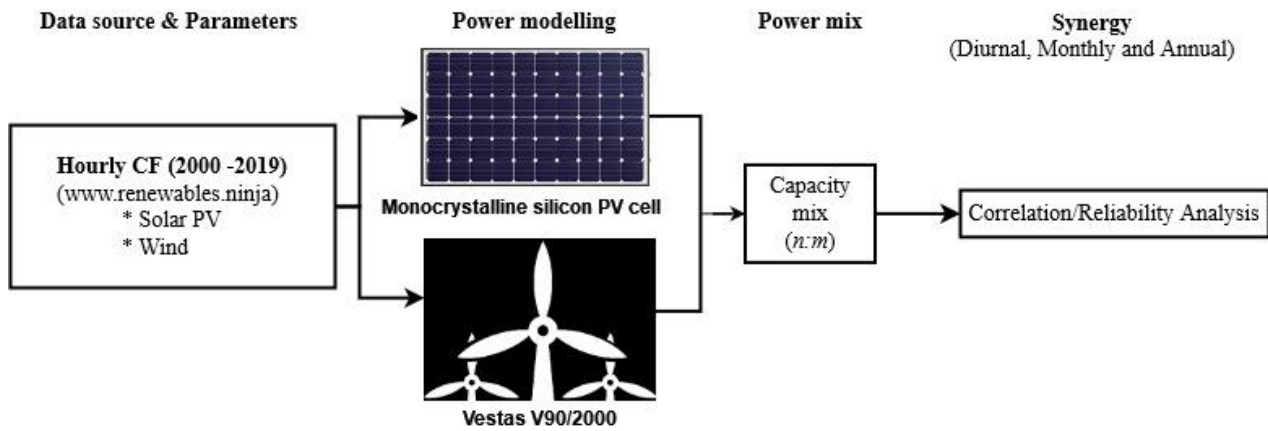


Fig. 1. Assessment Framework for Analyzing the Balance between Mean Capacity Factor (CF), Variability, and Supply Reliability

C. Wind Capacity Factors

The wind capacity factor (CF_w) of a Vestas V90-2000 wind turbine is modeled using the power curve equation shown in equation (1) [29]. CF_w is determined based on the hub height of the wind turbine.

$$CF_w = \begin{cases} 0 & \text{for } V \leq V_{in} \\ \frac{V^3 - v_{in}^3}{V_r^3 - v_{in}^3} & \text{for } V_{in} < V < V_r \\ 1 & \text{for } V_r < V < V_c \\ 0 & \text{for } V > V_c \end{cases} \quad (1)$$

In which the cut-in wind speed, V_{in} is taken to be equal to $3ms^{-1}$, the rated wind speed $V_r = 12ms^{-1}$ while the cut-off wind speed, V_c , is taken as $22.5ms^{-1}$ [30].

The most widely used wind turbine at Africa's largest wind power plant, the Lake Turkana Wind Power Plant, Vestas V90-2000, with a hub height of 90 meters and a power rating of 2 MW was chosen. The power curve model, utilized for estimating the capacity factor (CF) is as illustrated in Figure 2.

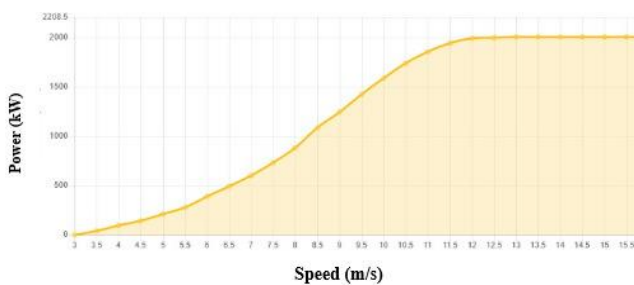


Fig. 2. Power Curve for Vestas V90/2000 Wind Turbine

D. Solar Photovoltaic Cells

The efficiency of solar cells, denoted as η_c , is represented as a function of global horizontal irradiation, G , and ambient air temperature, T , as depicted in equation (2) [31].

$$\eta_c(G, T) = \eta_{ref} \{ 1 - \beta(T_c(G, T) - T_{ref}) + \gamma \log_{10}(G) \} \quad (2)$$

In this equation, η_{ref} represents the reference efficiency, while the coefficients β and η correspond to the cell material and structure characteristics. Specifically, for monocrystalline silicon cells, the typical values used are $\beta = 0.0045$ and $\gamma = 0.1$. T_{ref} denotes the reference temperature ($25^\circ C$), and T_c signifies the cell temperature.

The solar PV capacity factor, denoted as CF_s , is hereby determined using equation (3) based on the modeling of cell efficiency.

$$CF_s = \frac{\eta_c(G, T).G}{\eta_{ref}.G_{ref}} \quad (3)$$

E. Normalized Kendall Tau Correlation Coefficient

In this study, we use a popular measure of correlation, Kendall tau (τ) to analyze the relationship between variables. This non-parametric rank-based measure of dependence is widely accepted and useful in diverse case scenarios.

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Kendall's tau is particularly useful when the data is not regularly distributed or contains outliers.

Its versatility makes it a useful tool for evaluating the correlations between variables in such scenarios [32]–[35].

The definition of Kendall's tau is based on the concept of concordance. Two sample elements (x_j, y_j) and (x_k, y_k) , from $\{(x_i, y_i)\}_{i=1}^n$ are considered concordant if $(x_j < y_j)$ and $(x_k < y_k)$ or $(x_j > y_j)$ and $(x_k > y_k)$ discordant if $(x_j < y_j)$ and $(x_k > y_k)$ or $(x_j > y_j)$ and $(x_k < y_k)$.

In a sample, there are $\binom{n}{2}$ distinct pairs of observations, each of which is either concordant or discordant. Designating 'c' as the number of concordant pairs and 'd' as the number of discordant pairs (i.e. $S = c - d$), the Kendall's tau for the sample can therefore be defined as:

$$\tau = \frac{c-d}{c+d} = \frac{s}{\binom{n}{2}} = \frac{2s}{n(n-1)} \quad (4)$$

The correlation coefficient, which typically ranges between -1 and +1, acts as a guide for understanding the complex relationships between variables [36]. When the values lie close to zero, it indicates minimal correlation, suggesting little synchrony between the paired sets of variables. However, as the coefficient moves towards either end of the spectrum, its significance becomes more pronounced.

In the case of variable renewable energy utilization, it is important to fully comprehend the correlation between different energy sources. Energy complementarity relies heavily on the correlation coefficient values, particularly when it comes to the interplay between various renewable resources such as wind and solar power. A positive correlation between the production of wind and solar energy indicates that when one resource experiences fluctuations, the other tends to as well fluctuate in the same fashion. Conversely, a negative correlation could indicate an inverse relationship between renewable energy sources. In such cases, when the production of one resource decreases, the output of the other increases, serving as a potential buffer against intermittency and enhancing the overall system resilience. A proper analysis of the correlation is essential in understanding the complex relationships of the available VRE resources, allowing analysts to make well-informed decisions and predictions based on the data at hand.

Hybrid systems operating in a complementarity mode can effectively minimize output fluctuations, thereby enhancing stability and ensuring greater supply reliability. Additionally, these hybrid systems offer the advantage of optimizing energy generation by utilizing multiple sources such as available solar and wind, further contributing to a sustainable and resilient power infrastructure.

F. LOLP

LOLP refers to Loss of Load Probability, which is a measure of the probability of a power system being unable to meet the demand. The total generated power is compared to the hourly demand to assess the system's ability to meet the load. If the demand exceeds the generated power, some loads may go unserved, resulting in a Loss of Load. The Loss of Load Probability (LOLP) is then calculated based on this comparison as captured in equation (5) [37]:

$$LOLP = \sum_i P[C < L_i]P[L_i] \quad (5)$$

Where, P denotes probability, C is the generation output ($p.u$) and L_i is load during the i^{th} time step.

G. Normalized Load Demanded and Power Output Intervals

The households in rural areas are the main consumers of the isolated systems spread across the area. We assume a constant normalized hourly load for these households. To calculate the loading probabilities, we divide the duration of a loading state by the total time (24 or 8760 hours), that is on a diurnal or annual timescale. The probability of wind and solar PV power output generation was based on wind speed and solar irradiation on a diurnal timescale and collated with an assumed equal power mix of wind and solar PV.

III. RESULTS AND DISCUSSIONS

A. Mean Annual Wind-Solar Power Resource Variability

A total of twenty sites were carefully chosen from a wide range of grid points to evaluate the degree of complementarity between wind and solar photovoltaic (PV) installations across the region. As shown in Figure 3, the wind-solar complementarity, τ_{ws} predominantly displays a negative trend across the region, indicating their synergistic relationship in output power generation. Furthermore, the level of complementarity tends to increase towards the northeastern regions when analyzed on an hourly basis across the year. This variation in space and time emphasizes the dynamics between wind and solar resources, highlighting the nuanced nature of their complementarity in improving power supply reliability in a diverse geographical context.

Figure 4 depicts the variation in output power exhibited by the two resources from the 20 selected grid sites. The graphical presentation illustrates the variability of spatial-temporal power potential in terms of Capacity Factor (CF) on an hourly timescale across the year. As observed, the average CF for solar energy spans from 16% to 19.5% annually, underscoring the consistent but modest solar power potential across the region. On the other hand, the average CF for wind energy ranges from 16% to 25%, showcasing a higher potential though with a wider spectrum of variability.

This levels underscores the diverse wind power potential inherent within the studied area, with certain locations consistently experiencing stronger winds and consequently higher CFs compared to others. Moreover, this variability in wind density throughout the year emphasizes the significance of comprehending temporal patterns to effectively optimize renewable energy generation strategies.

To counter the decreasing capacity value resulting from the increasing penetration of VREs amid high annual wind variation, distributed generation offers an effective approach. This strategy involves diversifying wind farm locations and

interconnecting sources across a large area, as demonstrated by Ssengonzi et al. [38].

Blending homogeneous wind resources allows wind speed variance to be levelled out, ultimately boosting wind peak capacity. Distributed generation has the added benefits of reducing wind curtailment and transmission congestion [39]. Furthermore, heterogeneous resource blending can lead to reduced inter-annual variability in peak net load values [40], while diversified VRE can enhance grid reliability as well as improve the overall performance of the energy system.

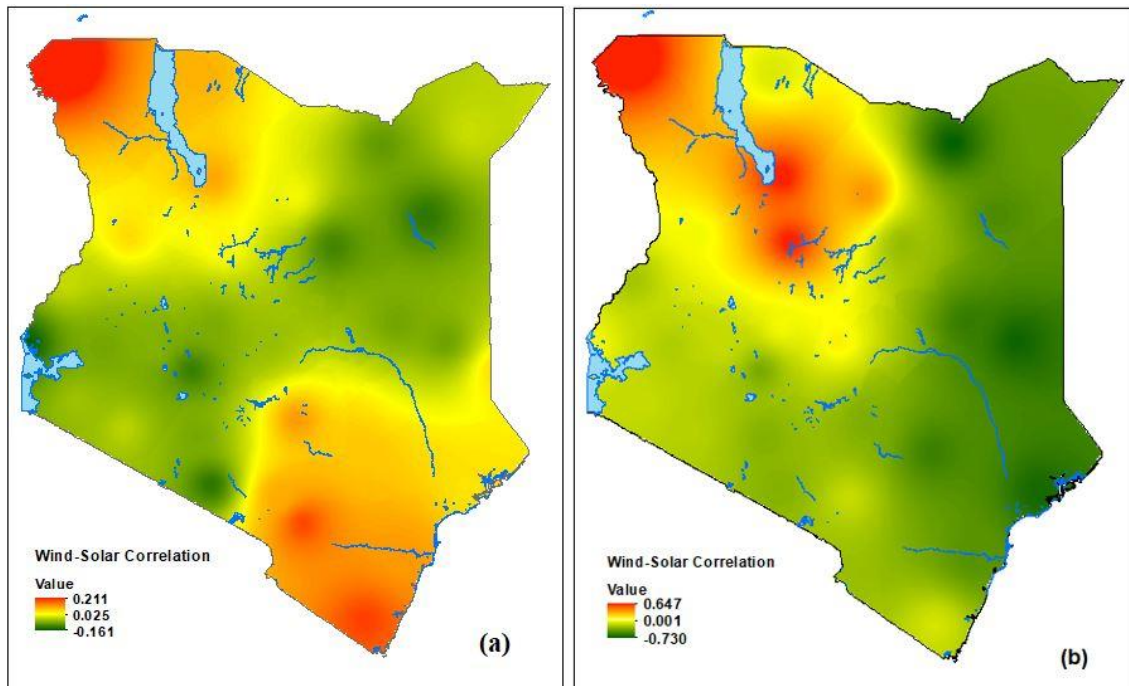


Fig. 3. Trends in the Correlation between Wind and Solar PV Power Output Capabilities

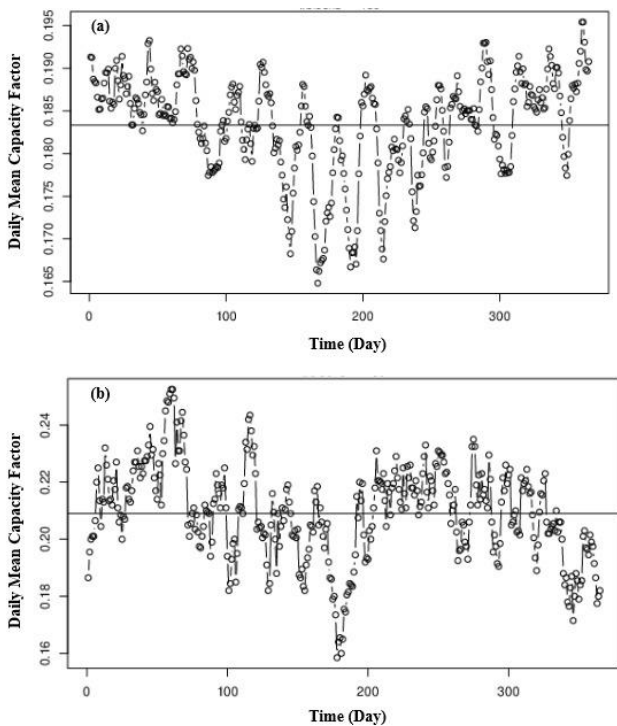


Fig. 4. The Annual Variability of Hourly Average Capacity Factors of Solar (a) and Wind (b) Power Generation Profiles of the Considered Sites

B. Mean Monthly Wind-Solar Power Resource Variability

Figure 5 provides an extensive assessment of the variability of wind power potential, displaying the capacity factor for each month. Solar capacity factor (CF) shows little variation in March and between September and October, with the latter period exhibiting the highest levels of CFs. This indicates a consistent solar power generation during these months, implying a potentially more reliable energy source during those times. In contrast, the months between June and September show a noticeable increase in wind CF fluctuation across the region as typically exhibited in the area during the onset of the rainy season.

The observed monthly trends in wind and solar PV performance, with higher values during the first quarter and lower values towards the end of the year, mirror the seasonal patterns prevalent in the Kenyan landscape [41]. This pattern is particularly pronounced in the northern and eastern regions, where two distinct wind seasons contribute significantly to renewable energy generation capacity.

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One of these wind seasons, as noted, occurs from December to March. During this period, the wind, originating from the northeast, blows steadily across the region. This wind is renowned for its availability and consistency, making it a valuable resource for wind energy production. Its predictable nature contributes to the higher performance values observed in wind energy generation during the corresponding months. Conversely, the second wind season occurs from June to September, characterized by the prevailing southerly trade winds. While the this wind season also contributes to an increase in output power generation, its intensity and monthly variability seen to be more pronounced

in comparison to earlier months. The seasonal alternation between these wind patterns, coupled with the inherent variability of solar energy, results in the observed monthly trends in hybrid renewable energy system performance. While both wind and solar PV exhibit fluctuations throughout the year, their patterns show some degree of similarity than complementarity, indicating minimal offsetting of each other's weaknesses. [Figure 6](#) displays a visualization of the resource potentials, showcasing the low-high trends on a monthly basis across the year. As noted, aggregating wind and solar PV generation reduces monthly variability by 12% signifying the integration benefits of hybrid systems.

Table-II: Probability of Wind and Solar PV Power Output Based on Wind Speed and Solar Irradiation on a Diurnal Timescale

Output Power Interval (p.u)	Wind		Solar		Hybrid	
	No. of Hours	Probability	No. of Hours	Probability	No. of Hours	Probability
0.00 - 0.0499	9	0.375	10	0.47619	8	0.380952
0.05 - 0.0999	11	0.458333	3	0.142857	4	0.190476
0.10 - 0.1499	3	0.125	1	0.047619	2	0.095238
0.15 - 0.1999	1	0.041667	1	0.047619	1	0.047619
0.20 - 0.2499	-	-	1	0.047619	2	0.095238
0.25 - 0.2999	-	-	2	0.095238	3	0.142857
0.30 - 0.3499	-	-	3	0.142857	3	0.142857
0.35 - 0.3999	-	-	3	0.142857	2	0.095238
0.40 - 0.4499	-	-	-	-	-	-
0.45 - 0.4999	-	-	-	-	-	-
0.50 - 0.5499	-	-	-	-	-	-
0.55 - 0.5999	-	-	-	-	-	-
Total	24	1.0	24	1.0	24	1.0

Table-III: Probability of Wind and Solar PV Power Output Based on Wind Speed and Solar Irradiation on a Seasonal Timescale

Output Power Interval (p.u)	Wind		Solar		Hybrid	
	No. of Hours	Probability	No. of Hours	Probability	No. of Hours	Probability
0.00 - 0.0499	563	0.064269	4809	0.548973	450	0.05137
0.05 - 0.0999	507	0.057877	323	0.036872	601	0.068607
0.10 - 0.1499	690	0.078767	238	0.027169	809	0.092352
0.15 - 0.1999	691	0.078881	273	0.031164	874	0.099772
0.20 - 0.2499	599	0.068379	212	0.024201	900	0.10274
0.25 - 0.2999	491	0.05605	252	0.028767	886	0.101142
0.30 - 0.3499	442	0.050457	258	0.029452	911	0.103995
0.35 - 0.3999	432	0.049315	334	0.038128	992	0.113242
0.40 - 0.4499	436	0.049772	374	0.042694	708	0.080822
0.45 - 0.4999	411	0.046918	427	0.048744	420	0.047945
0.50 - 0.5499	380	0.043379	308	0.03516	343	0.039155
0.55 - 0.5999	399	0.045548	297	0.033904	296	0.03379
0.60 - 0.6499	344	0.039269	266	0.030365	277	0.031621
0.65 - 0.6999	399	0.045548	231	0.02637	204	0.023288
0.70 - 0.7499	408	0.046575	149	0.017009	78	0.008904
0.75 - 0.7999	469	0.053539	9	0.001027	11	0.001256
0.80 - 0.8499	445	0.050799	0	0	0	0
0.85 - 0.8999	394	0.044977	0	0	0	0
0.90 - 0.9499	233	0.026598	0	0	0	0
0.95 - 1.0000	27	0.003082	0	0	0	0
Total	8760	1.0	8760	1.0	8760	1.0



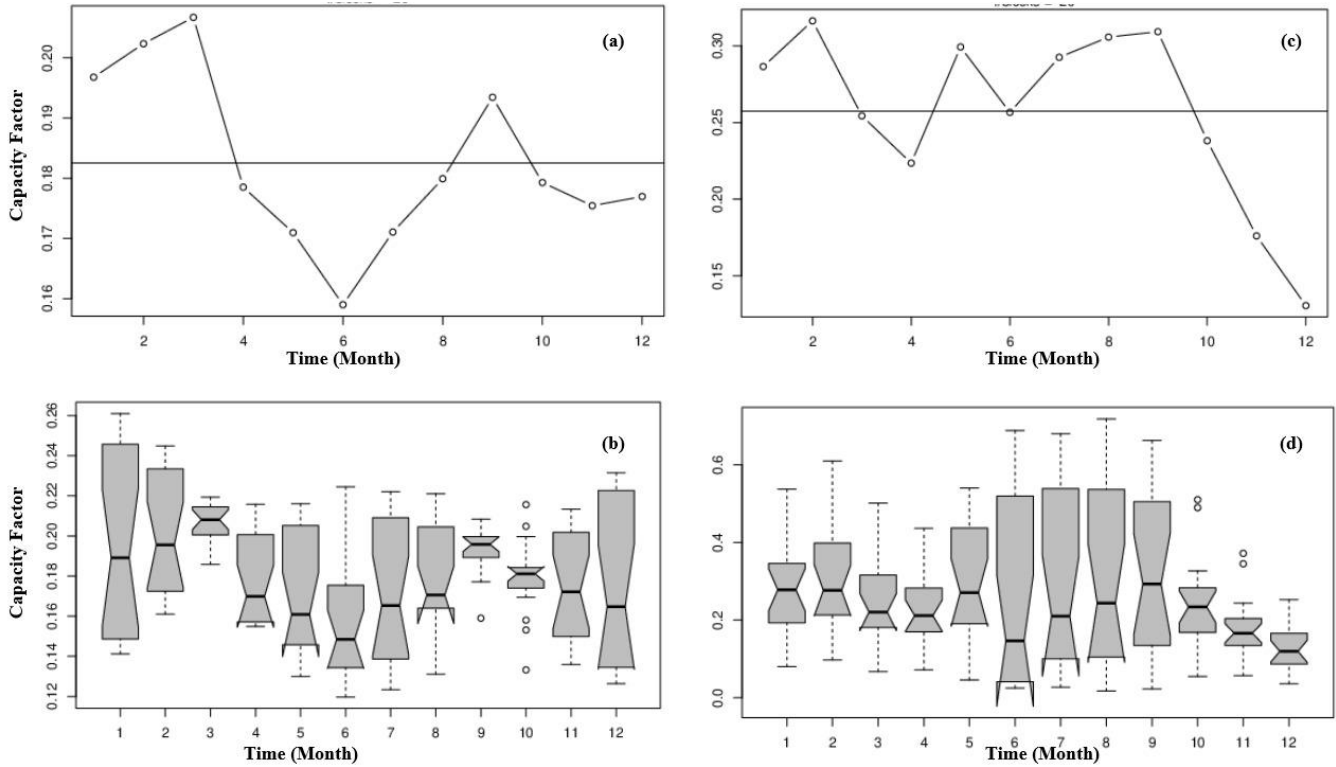


Fig. 5. The Monthly Variability of Hourly Average Capacity Factors of Solar (A And B) and Wind (C & D) Power Generation Profiles of the Selected Sites Across the Region

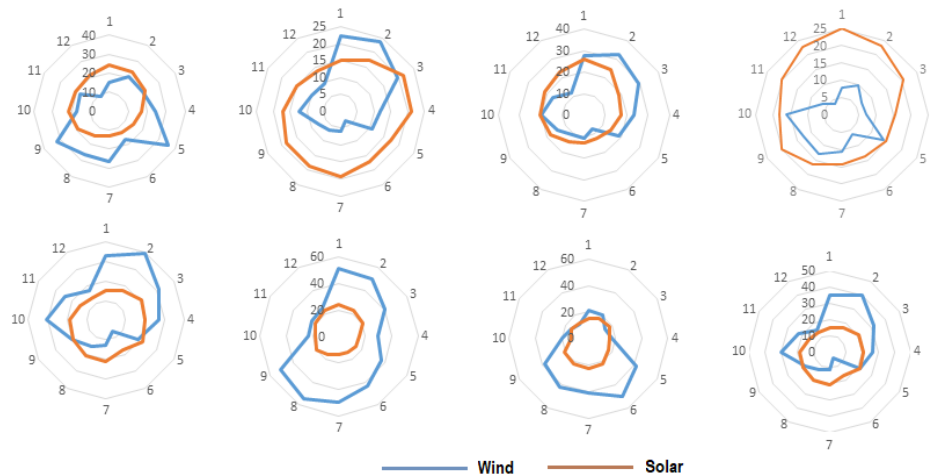


Fig. 6. The annual Variability of the Mean Monthly Capacity Factors of Wind and Solar Power Generation Profiles of the Sampled Sites

C. Diurnal Wind-Solar Power Resource Variability

Assessing system reliability heavily relies on the daily variability of resources, underscoring the level of its critical importance. The graph in Figure 7 illustrates the variability in resource availability across the study area, with data sampled from 20 grid points. This daily variability is notably location-specific, with each site exhibiting its unique pattern of resource availability.

The time of day is also of great significance. Notably, the graph highlights a broader deviation in resource availability for solar energy, particularly during mid-day periods. This observation aligns with the inherent nature of solar energy, which is heavily influenced by factors such as cloud cover, atmospheric conditions, and the angle of sunlight. As a result, solar energy generation tends to exhibit more pronounced fluctuations, especially during peak daylight hours when

solar irradiance is at its highest.

As noted, wind and solar PV display a remarkable level of complementarity, with a range stretching between -0.1097 and -0.5898. This indicates that when solar energy production is at its peak during the day, wind energy production is relatively low, and vice versa.

Such a complementary nature ensures a steady and dependable flow of renewable energy, thereby enhancing the power supply reliability as a result of reduced variability in energy production. As a result, the combined use of wind and solar PV energy sources can contribute to a more stable and resilient system.

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The significant improvement in hybrid system performance, evidenced by the increased diurnal capacity

factor and up to a 20% reduction in output variability affirms these benefits.

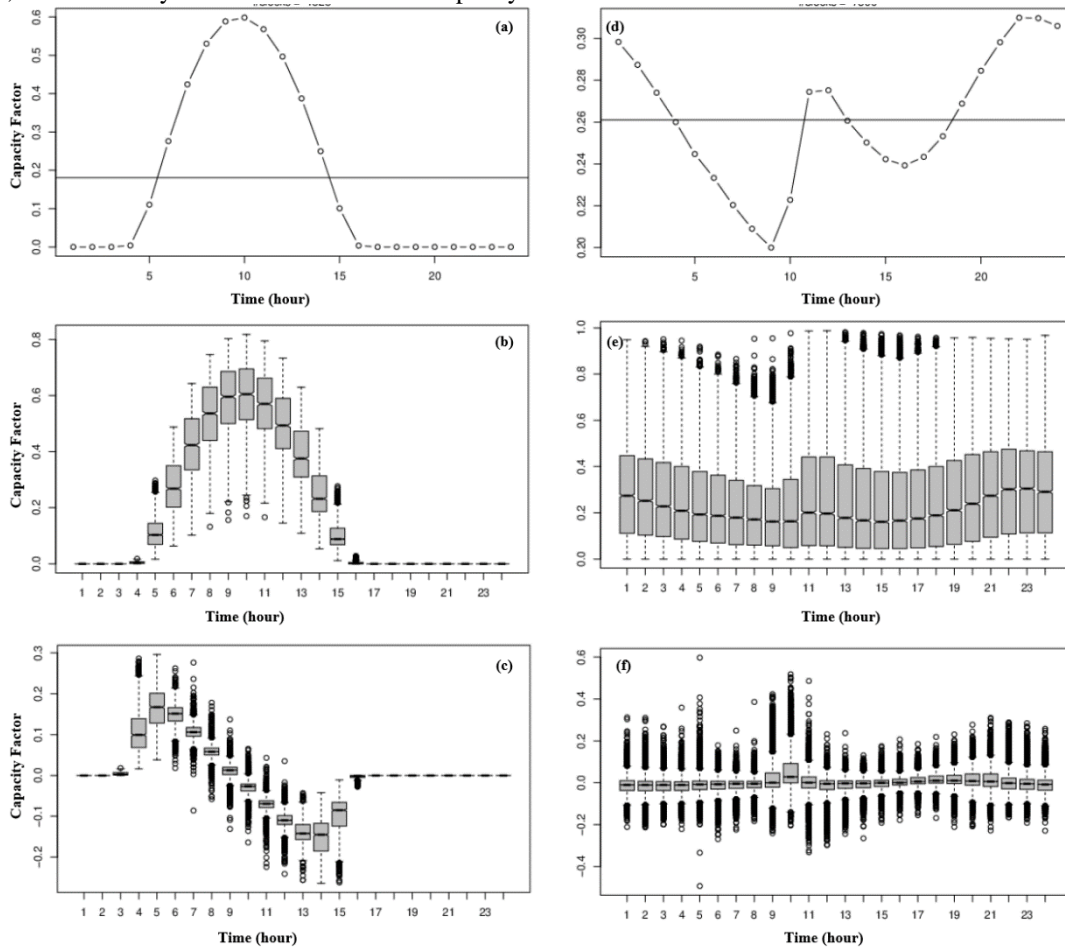


Fig. 7. The Diurnal Variability of Mean Hourly Capacity Factors of Solar PV (a) – (c) and Wind (d) – (f) Power Generation Profiles of the Selected Sites

D. Effect of the Complementarity Index on the System Reliability

Figure 8 displays scatter plots that visually depict the relationship between resource complementarity and system reliability, as measured by LOLP. The data clearly demonstrates that greater temporal complementarity among resources corresponds to increased system reliability. By analyzing the gradients of the curves in the scatter plots, it becomes apparent that variations in the complementarity of wind-solar PV resources in the region can enhance LOLP significantly between 5% to 16%.

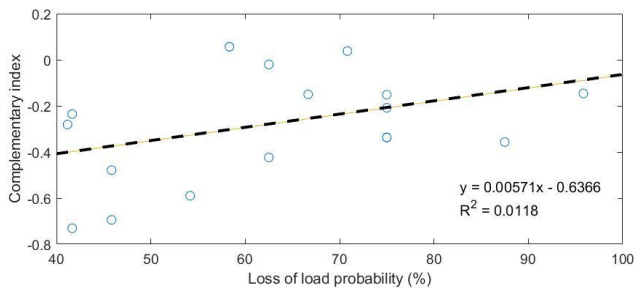


Fig. 8. Complementarity Index in Relation to Loss of Load Probability

These findings suggest that optimizing the temporal complementarity of renewable resources can play a crucial role in improving the overall reliability of the energy system.

Furthermore, the observed range of improvement in LOLP highlights the potential benefits of strategically integrating wind and solar PV resources in a way that maximizes their complementarity. This approach enables the planners to leverage on strengths of each resource in a coordinated manner, leading to a more robust and resilient energy system.

IV. CONCLUSIONS AND FURTHER PROSPECTS

This analysis highlights the significant role of variable energy sources in enhancing supply reliability through complementarity. From the results, examining the synergy between the available different renewable energy sources, such as solar and wind, it becomes evident that their variability can be balanced to ensure more consistent power generation. This complementary relationship not only helps mitigate the intermittency associated with individual sources but also contributes to overall system stability and reliability. Similarly, the study highlights the need for a holistic approach that gradually implements an optimal mix rather than focusing solely on predominant sources, thus maximizing their potential while minimizing associated drawbacks.

Therefore, leveraging strategically the complementarity of variable energy sources emerges as a crucial strategy for improving supply reliability in energy systems.

The results affirms that integration of wind resources across the entire area of study provides even greater potential benefits compared to solar resource. Moreover, these benefits span across all timescales, from diurnal, monthly and annually, thus highlighting the complementary nature of wind and solar energy. By strategically deploying optimal capacities, the existing synergy can effectively address the issue of resource variability and hence enhance the energy supply reliability. Furthermore, the study affirms that the benefits of spatial integration at an hourly timescale are more pronounced comparatively.

In conclusion, streamlining renewable energy integration in long-term planning for rural electrification can play a crucial role in achieving sustainable development goals through enhanced electrification of the diverse Kenyan remote regions. This can help reduce dependency on fossil fuels and accelerate the path towards lowering the overall carbon footprint of the country's energy sector.

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Availability of Data and Material	Not required.
Authors Contributions	Each author has made an independent contribution to the article. The individual contributions of each author are presented below for clarity and transparency. D.J. conducted literature survey, collected, processed and analyzed the data, and drafted the manuscript. J.M. and C.K. edited and reviewed the manuscript. All authors have read and consented for publication.

REFERENCES

1. P. Gertler, K. Lee, and A. M. Mobarak, "Electricity Reliability and Economic Development in Cities: A Microeconomic Perspective," 2017. [Online]. Available: <https://api.semanticscholar.org/CorpusID:55782393>
2. P. K. Painuly, R. Tyagi, S. Vishwakarma, S. K. Khare, and M. Haghighi, "Energy Supply Using Nexus Approach for Attaining Sustainable Development Goal 7," in *Affordable and Clean Energy*, W. Leal Filho, A. Marisa Azul, L. Brandli, A. Lange Salvia, and T. Wall, Eds., Cham: Springer International Publishing, 2021, pp. 562–573. doi: 10.1007/978-3-319-95864-4_84. https://doi.org/10.1007/978-3-319-95864-4_84
3. K. Qiu and E. Entchev, "Modeling, design and optimization of integrated renewable energy systems for electrification in remote communities," *Sustain. Energy Res.*, vol. 11, no. 1, Mar. 2024, doi: 10.1186/s40807-024-00103-5. <https://doi.org/10.1186/s40807-024-00103-5>

4. S. M. Mahmoudi, A. Maleki, and D. R. Ochbelagh, "Optimization of a hybrid energy system with/without considering back-up system by a new technique based on fuzzy logic controller," *Energy Convers. Manag.*, vol. 229, p. 113723, 2021, doi: <https://doi.org/10.1016/j.enconman.2020.113723>
5. H. Liu, D. Li, Y. Liu, M. Dong, X. Liu, and H. Zhang, "Sizing Hybrid Energy Storage Systems for Distributed Power Systems under Multi-Time Scales," *Appl Sci*, vol. 8, no. 9, p. 1453, Aug. 2018, doi: 10.3390/app8091453. <https://doi.org/10.3390/app8091453>
6. H. Liu, B. Wu, A. Maleki, F. Pourfayaz, and R. Ghasempour, "Effects of Reliability Index on Optimal Configuration of Hybrid Solar/Battery Energy System by Optimization Approach: A Case Study," *Int J Photoenergy*, vol. 2021, Oct. 2021, doi: 10.1155/2021/9779996. <https://doi.org/10.1155/2021/9779996>
7. M. J. Abed and A. Mhalla, "Reliability assessment of grid-connected multi-inverter for renewable power generation sector," *Arab Gulf J. Sci. Res.*, Feb. 2023, doi: 10.1108/agjrs-08-2022-0149. <https://doi.org/10.1108/AGJSR-08-2022-0149>
8. C. E. Hoicka and I. H. Rowlands, "Solar and wind resource complementarity: Advancing options for renewable electricity integration in Ontario, Canada," *Renew. Energy*, vol. 36, no. 1, pp. 97–107, Jan. 2011, doi: 10.1016/j.renene.2010.06.004.
9. F. Monforti, T. Huld, K. Bifmmode(acuteo)elseo(fidis, L. Vitali, M. D'Isidoro, and R. Lacal-Artegui, "Assessing complementarity of wind and solar resources for energy production in Italy. A Monte Carlo approach," *Renew. Energy*, vol. 63, pp. 576–586, Mar. 2014, doi: 10.1016/j.renene.2013.10.028. <https://doi.org/10.1016/j.renene.2010.06.004>
10. P. de Jong, A. S. Sanchez, K. Esquerre, R. A. Kalid, and E. A. Torres, "Solar and wind energy production in relation to the electricity load curve and hydroelectricity in the northeast region of Brazil," *Renew. Sustain. Energy Rev.*, vol. 23, pp. 526–535, Jul. 2013, doi: 10.1016/j.rser.2013.01.050. <https://doi.org/10.1016/j.renene.2013.10.028>
11. S. Park and S. R. Salkuti, "Optimal Energy Management of Railroad Electrical Systems with Renewable Energy and Energy Storage Systems," *Sustainability*, vol. 11, no. 22, p. 6293, Nov. 2019, doi: 10.3390/su11226293. <https://doi.org/10.1016/j.rser.2013.01.050>
12. A. Sankaran et al., "Multifractal Cross Correlation Analysis of Agro-Meteorological Datasets (Including Reference Evapotranspiration) of California, United States," *Atmosphere*, vol. 11, no. 10, p. 1116, Oct. 2020, doi: 10.3390/atmos11101116. <https://doi.org/10.3390/atmos11101116>
13. F. J. Santos-Alamillos, D. Pozo-Vzquez, J. A. Ruiz-Arias, V. Lara-Fanego, and J. Tovar-Pescador, "Analysis of Spatiotemporal Balancing between Wind and Solar Energy Resources in the Southern Iberian Peninsula," *J. Appl. Meteorol. Climatol.*, vol. 51, no. 11, pp. 2005–2024, Nov. 2012, doi: 10.1175/JAMC-D-11-0189.1. <https://doi.org/10.1175/JAMC-D-11-0189.1>
14. H. M. Osofsky, "Modeling and Assessment of Wind and Insolation Resources with a Focus on Their Complementary Nature: A Case Study of Oklahoma," in *The New Geographies of Energy*, Routledge, 2013, pp. 28–40. doi: 10.4324/9780203722299-8. <https://doi.org/10.4324/9780203722299-8>
15. D. Harrison-Atlas, C. Murphy, A. Schleifer, and N. Grue, "Temporal complementarity and value of wind-PV hybrid systems across the United States," *Renew. Energy*, vol. 201, pp. 111–123, Dec. 2022, doi: 10.1016/j.renene.2022.10.060. <https://doi.org/10.1016/j.renene.2022.10.060>
16. A. Couto and A. Estanqueiro, "Assessment of wind and solar PV local complementarity for the hybridization of the wind power plants installed in Portugal," *J Clean. Prod.*, vol. 319, p. 128728, Oct. 2021, doi: 10.1016/j.jclepro.2021.128728. <https://doi.org/10.1016/j.jclepro.2021.128728>
17. P. E. Bett and H. E. Thornton, "The climatological relationships between wind and solar energy supply in Britain," *Renew. Energy*, vol. 87, pp.



Characterizing Supply Reliability Through the Synergistic Integration of VRE towards Enhancing Electrification in Kenya

- 96–110, Mar. 2016, doi: 10.1016/j.renene.2015.10.006. <https://doi.org/10.1016/j.renene.2015.10.006>
18. R. Castro and J. Crispim, “Variability and correlation of renewable energy sources in the Portuguese electrical system,” *Energy Sustain. Dev.*, vol. 42, pp. 64–76, Feb. 2018, doi: 10.1016/j.esd.2017.10.005. <https://doi.org/10.1016/j.esd.2017.10.005>
19. H. D. Puspitarini, B. Francois, M. Zaramella, C. Brown, and M. Borgia, “The impact of glacier shrinkage on energy production from hydropower-solar complementarity in alpine river basins,” *Sci Total Env.*, vol. 719, p. 137488, Jun. 2020, doi: 10.1016/j.scitotenv.2020.137488. <https://doi.org/10.1016/j.scitotenv.2020.137488>
20. A. Beluco, P. Kroeff de Souza, and A. Krenzinger, “A method to evaluate the effect of complementarity in time between hydro and solar energy on the performance of hybrid hydro PV generating plants,” *Renew. Energy*, vol. 45, pp. 24–30, Sep. 2012, doi: 10.1016/j.renene.2012.01.096. <https://doi.org/10.1016/j.renene.2012.01.096>
21. P. C. S. Borba, W. C. Sousa, M. Shadman, and S. Pfenninger, “Enhancing drought resilience and energy security through complementing hydro by offshore wind power in mode—else—fi The case of Brazil,” *Energy Convers Manage*, vol. 277, p. 116616, Feb. 2023, doi: 10.1016/j.enconman.2022.116616. <https://doi.org/10.1016/j.enconman.2022.116616>
22. K. J. Nyoni, A. Maronga, P. G. Tuohy, and A. Shane, “Hydro-Connected Floating PV Renewable Energy System and Onshore Wind Potential in Zambia,” *Energies*, vol. 14, no. 17, p. 5330, Aug. 2021, doi: 10.3390/en14175330. <https://doi.org/10.3390/en14175330>
23. H. I. Jager, R. A. Efrogmson, and R. A. McManamay, “Renewable energy and biological conservation in a changing world,” *Biol Conserv.*, vol. 263, p. 109354, Nov. 2021, doi: 10.1016/j.biocon.2021.109354. <https://doi.org/10.1016/j.biocon.2021.109354>
24. J. Jurasz, J. Mikulik, M. Krzywda, B. Ciapala, and M. Janowski, “Integrating a wind- and solar-powered hybrid to the power system by coupling it with a hydroelectric power station with pumping installation,” *Energy*, vol. 144, pp. 549–563, Feb. 2018, doi: 10.1016/j.energy.2017.12.011. <https://doi.org/10.1016/j.energy.2017.12.011>
25. A. Kies, B. U. Schyska, and L. von Bremen, “The Effect of Hydro Power on the Optimal Distribution of Wind and Solar Generation Facilities in a Simplified Highly Renewable European Power System,” *Energy Procedia*, vol. 97, pp. 149–155, Nov. 2016, doi: 10.1016/j.egypro.2016.10.043. <https://doi.org/10.1016/j.egypro.2016.10.043>
26. A. Risso, A. Beluco, and R. D. C. Marques Alves, “Complementarity Roses Evaluating Spatial Complementarity in Time between Energy Resources,” *Energies*, vol. 11, no. 7, p. 1918, Jul. 2018, doi: 10.3390/en11071918. <https://doi.org/10.3390/en11071918>
27. G. Ren *et al.*, “Investigating the Complementarity Characteristics of Wind and Solar Power for Load Matching Based on the Typical Load Demand in China,” *IEEE Trans. Sustain. Energy*, vol. 13, no. 2, pp. 778–790, Apr. 2022, doi: 10.1109/tste.2021.3131560.
28. J. Jurasz, F. A. Canales, A. Kies, M. Guezgouz, and A. Beluco, “A review on the complementarity of renewable energy sources: Concept, metrics, application and future research directions,” *Sol. Energy*, vol. 195, pp. 703–724, Jan. 2020, doi: 10.1016/j.solener.2019.11.087.
29. E. Nyenah, S. Sterl, and W. Thiery, “Pieces of a puzzle: solar-wind power synergies on seasonal and diurnal timescales tend to be excellent worldwide,” *Environ. Res. Commun.*, vol. 4, no. 5, p. 055011, May 2022, doi: 10.1088/2515-7620/ac71fb. <https://doi.org/10.1088/2515-7620/ac71fb>
30. “<https://en.wind-turbine-models.com/turbines/16-vestas-v90>”
31. S. Dubey, J. Sarvaiya, and B. Seshadri, “Temperature Dependent Photovoltaic (PV) Efficiency and Its Effect on PV Production in the World – A Review,” *Energy Procedia*, vol. 33, pp. 311–321, Dec. 2013, doi: 10.1016/j.egypro.2013.05.072.
32. M. G. KENDALL, “A NEW MEASURE OF RANK CORRELATION,” *Biometrika*, vol. 30, no. 1–2, pp. 81–93, Jun. 1938, doi: 10.1093/biomet/30.1-2.81. <https://doi.org/10.1093/biomet/30.1-2.81>
33. “Kendall tau metric - Encyclopedia of Mathematics.” Aug. 2023. [Online]. Available: https://encyclopediaofmath.org/index.php?title=Kendall_tau_metric
34. P. Wessa, “Kendall tau Rank Correlation (v1.0.13) in Free Statistics Software (v1.2.1), Office for Research Development and Education,” 2017. [Online]. Available: URL https://www.wessa.net/rwasp_kendall.wasp/
35. D. Kokol Bukovšek and N. Stopar, “On the Exact Regions Determined by Kendall’s Tau and Other Concordance Measures,” *Mediterr. J. Math.*, vol. 20, no. 3, Feb. 2023, doi: 10.1007/s00009-023-02350-0. <https://doi.org/10.1007/s00009-023-02350-0>
36. F. A. Canales, J. Jurasz, A. Beluco, and A. Kies, “Assessing temporal complementarity between three variable energy sources through correlation and compromise programming,” *Energy*, vol. 192, p. 116637, Feb. 2020, doi: 10.1016/j.energy.2019.116637. <https://doi.org/10.1016/j.energy.2019.116637>
37. Y. K. Putri and A. Adrianti, “Calculation of Photovoltaic Reliability for Assessing Loss of Load Probability,” in *2020 7th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)*, 2020, pp. 230–235. doi: 10.1109/ICITACEE50144.2020.9239171. <https://doi.org/10.1109/ICITACEE50144.2020.9239171>
38. J. Ssengonzi, J. X. Johnson, and J. F. DeCarolis, “An efficient method to estimate renewable energy capacity credit at increasing regional grid penetration levels,” *Renew. Sustain. Energy Transit.*, vol. 2, p. 100033, 2022, doi: <https://doi.org/10.1016/j.rset.2022.100033>
39. Novacheck and J. X. Johnson, “Diversifying wind power in real power systems,” *Renew. Energy*, vol. 106, pp. 177–185, Jun. 2017, doi: 10.1016/j.renene.2016.12.100. <https://doi.org/10.1016/j.renene.2016.12.100>
40. T. H. Ruggles and K. Caldeira, “Wind and solar generation may reduce the inter-annual variability of peak residual load in certain electricity systems,” *Appl. Energy*, vol. 305, p. 117773, Jan. 2022, doi: 10.1016/j.apenergy.2021.117773. <https://doi.org/10.1016/j.apenergy.2021.117773>
41. H. C. Bloomfield, C. M. Wainwright, and N. Mitchell, “Characterizing the variability and meteorological drivers of wind power and solar power generation over Africa,” *Meteorol. Appl.*, vol. 29, no. 5, Sep. 2022, doi: 10.1002/met.2093. <https://doi.org/10.1002/met.2093>
42. Das, N. K., Saikia, P. M., Buragohain, Dr. M., & Saikia, N. (2022). An Adaptive Controller Design using Duelist Optimization Algorithm for an Interconnected Power System. In *International Journal of Engineering and Advanced Technology* (Vol. 11, Issue 4, pp. 1–15). <https://doi.org/10.35940/ijeat.d3410.0411422>
43. Ramani, P. R., Shariff, S. M., & Brahmam, M. N. V. V. (2020). PV-Hess Based Zeta Converter for BLDC Motor Drive using Fuzzy Logic Controller. In *International Journal of Innovative Technology and Exploring Engineering* (Vol. 9, Issue 3, pp. 1455–1460). <https://doi.org/10.35940/ijtee.b7828.019320>
44. Srivastava, S., & Maurya, Dr. S. (2019). Fuel efficiency optimization Techniques in Hybrid Vehicle. In *International Journal of Recent Technology and Engineering (IJRTE)* (Vol. 8, Issue 3, pp. 6790–6799). <https://doi.org/10.35940/ijrte.c5160.098319>

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