International Journal of Sustainable Energy Planning and Management Vol. 50 2026 4–19

International Journal of
Sustainable Energy Planning and Management

Optimal sizing of wind and solar hybrid renewable energy systems under grid constraints: A Brazilian case study

Levi Freitas Fernandes Távora*, Danielle Costa Morais

Department of Production Engineering, Universidade Federal de Pernambuco (UFPE), Av. Prof. Moraes Rego, 1235, Cidade Universitária, Recife, PE 50670-901, Brazil.

ABSTRACT

The increasing demand for clean and cost-effective energy has driven the development of hybrid renewable energy systems, particularly those combining wind and solar power. This paper introduces a practical optimization model for sizing hybrid onshore wind and photovoltaic power plants, incorporating critical systemic constraints such as land availability, grid capacity, and natural complementarity between energy sources. Unlike traditional models focused solely on minimizing cost or maximizing energy output, this approach considers the temporal anti-correlation between wind and photovoltaic resources to enhance grid infrastructure utilization. Developed in Microsoft Excel® with the Solver add-in, the model is accessible and easy to implement for energy planners and developers. A real case study in Sento Sé, Bahia State in Brazil, where wind and solar generation patterns are strongly anticorrelated, demonstrates the effectiveness of the model. Results indicate that the proposed hybrid configuration reduced the annualized system cost from 237.6 M USD to 161.6 M USD compared to standalone wind solution, representing a cost reduction of approximately 32%. Furthermore, grid infrastructure utilization increased from 64% to 84%, highlighting the benefit of incorporating resource complementarity into the system sizing. These outcomes highlight the value of well-designed hybrid systems, maximizing renewable integration without overloading existing infrastructure. The model offers a replicable decision-making tool for early-stage project design and capacity expansion planning, supporting more efficient and sustainable energy transitions.

Keywords

Hybrid power plants;
Grid constraints;
Wind energy;
Solar energy;
Linear programming

http://doi.org/10.54337/ijsepm.11379

1. Introduction

The growing impacts of climate change, combined with the pressing need for energy security and economic stability, have accelerated global conversation on transforming our energy systems. In this context, renewable energy sources are emerging not just as alternatives to fossil fuels, but as drivers of a broader shift in how we relate to the environment, the economy and society [1].

In recent years, the expansion of wind and solar power has reached unprecedented levels, driven by climate policy commitments and declining technology costs. As renewable penetration increases, hybrid renewable energy systems have emerged as a strategic solution to enhance system flexibility, reduce greenhouse gas emissions, and improve the utilization of existing transmission infrastructure [2-3]. Recent large-scale analyses indicate that coordinated hybrid deployment can mitigate curtailment, lower balancing requirements, and improve techno and economic performance compared to standalone installations [4-5].

The escalating global demand for energy, coupled with growing environmental concerns and the need for energy security, has positioned renewable energy sources at the forefront of power generation strategies [6-7]. Among these, wind and solar energy have emerged as two of the most viable and rapidly expanding

*Corresponding author – e-mail: levifft@hotmail.com

Received 13.02.2026 | Accepted 20.05.2026 | Published 03.08.2026

List of Abbreviations

PV	*Photovoltaic*
MILP	*Mixed Integer Linear Programming*
CapEx	*Capital Expenditure*
OpEx	*Operational Expenditure*
ONS	*National System Operator*
EPE	*Energy Research Company*

technologies. However, the inherent intermittency of these resources poses a significant challenge to their reliable and consistent supply of power [8]. To mitigate this limitation and harness the synergistic benefits of different renewable sources, hybrid renewable energy systems, integrating technologies such as wind turbines and photovoltaic arrays, have gained increasing attention [9-10]. Hybrid systems can leverage the complementary nature of wind and solar resources, potentially leading to a more stable and dependable energy output, as well as a more efficient use of electricity transmission and distribution infrastructure throughout the year.

For sustainable development, the reliance on the use of renewable energy sources has become essential. The proper selection of renewable energy resources, as well as the optimal sizing, are essential and challenging tasks in the design of renewables systems.

One of the challenges faced by developers and designers of renewable energy plants is the identification and definition of the best resource, or combination of resources, to maximize productivity, site constraints, energetic resources and infrastructure available. A critical aspect in the successful deployment of hybrid renewable energy systems is the optimal determination of their component sizes [11-14]. Inappropriately sized systems can lead to inefficiencies, increased costs, and compromised reliability.

Despite an increasing proportion of renewables in total energy consumption, an equitable transition from non-renewable to renewable energy is challenging due to the substantial rise in energy usage resulting from industrialization, urbanization, and globalization in recent decades [15].

In this context, hybrid renewable energy systems have emerged as a viable solution for both off-grid and grid-connected applications, as they can better accommodate the variability of natural resources while meeting electricity demand. Over the past two decades, interest in hybrid systems has grown significantly, consequently, various optimization techniques have been explored in the literature to address the challenge of optimal sizing for hybrid renewable energy systems. Among these, mathematical programming models, particularly those based on linear programming and mixed-integer linear programming, have proven to be effective tools for designing cost-efficient and reliable hybrid renewable energy systems [3, 6, 12, 16]. These models allow for the consideration of various factors, including load requirements, resource availability, economic parameters, and operational constraints, to identify the optimal configuration of the hybrid system.

The design of hybrid renewable energy system can be modelled as an optimization problem, in which the objective is to identify the most suitable combination and sizing of energy sources under technical, economic, and operational constraints. Over the past decades, the use of mathematical optimization and computer-based simulation techniques has become a well-established and effective approach for addressing the complexity inherent to such systems [11, 17].

To cope with the wide range of decision variables and constraints involved in hybrid system design, numerous optimization methods have been developed, including linear programming, mixed-integer linear programming, and multi-objective formulations [6, 12, 18]. These mathematical models provide a structured representation of complex systems, enabling the systematic evaluation of sizing and source allocation alternatives for hybrid renewable energy systems.

The use of optimization models is particularly justified in contexts where many feasible configurations exist, requiring the assessment of multiple trade-offs to identify the optimal or near-optimal solution [11,19]. This modeling approach complements heuristic or rule-based design methods, which rely primarily on empirical knowledge and engineering judgment. By combining formal optimization techniques with expert insight, decision-support models enhance transparency, consistency, and robustness in the planning and design of hybrid renewable energy systems [12].

A substantial body of literature has applied linear and mixed-integer programming models to support the design of hybrid renewable energy systems [11-12, 19]. Several studies also incorporate technical constraints such as land use, load requirements, and, in some cases, grid connection limits [3, 20]. In parallel, other research streams investigate wind and solar complementarity from statistical or planning perspectives [10, 21]. However, despite these advances, the explicit integration of temporal resource complementarity within a linear programming sizing model under binding grid capacity constraints, with the objective of improving both cost performance and grid infrastructure utilization, remains comparatively underexplored, particularly in practical, developer-oriented formulations suitable for early-stage project planning.

Therefore, it is important to advance in research and development of decision support models that can allow productivity gains and better use of the energy transmission and distribution infrastructure, which is a scarce resource with inefficient use. Combining different energy resources, considering infrastructure and energy resource constraints is a relevant problem to be solved.

This paper aims to introduce an optimization model for sizing hybrid renewable power plants that combine wind and solar energy sources, considering infrastructure and energy resource constraints. It specifically applies to a linear programming approach to determine the most cost-effective configuration of such a system while meeting a defined energy demand. To demonstrate the practical applicability and effectiveness of the proposed methodology, the study incorporates a case study in Sento Sé, Bahia State in Brazil. The results of this case study provide valuable insights into the optimal component sizing and the economic viability of wind-solar hybrid renewable power plants under real conditions. Applying the proposed model, this study provides a systematic approach for stakeholders to make decisions regarding the deployment of these sustainable energy solutions.

The paper is organized as follows: Section 2 provides a literature review on optimal sizing methodologies for hybrid wind-solar renewable energy systems; Section 3 introduces the novelty of the proposed methodology approach, highlighting the integration of grid constraints and resource complementarity; Section 4 presents the detailed formulation of the methodology approach and the linear programming model; Section 5 describes the case study and discusses the results; and Section 6 concludes the paper with final remarks and recommendations for future research.

2. Optimal sizing hybrid wind and solar renewable power plants

Hybrid renewable energy systems have been increasingly investigated as an alternative to standalone generation, since individual renewable sources may not provide the best solution in terms of cost, efficiency, and reliability. By combining different energy resources, particularly wind and solar hybrid systems can mitigate resource intermittency, improve energy yield, and enhance the utilization of available infrastructure. Consequently, a substantial body of literature has emerged addressing the optimal sizing and configuration of hybrid wind and solar power plants using a variety of optimization approaches.

Within the energy planning field, several studies emphasize the importance of integrated energy system planning, combining infrastructure constraints, modelling approaches, and renewable resource integration [22-24]. In this context, the present study contributes by explicitly incorporating grid constraints and resource complementarity into the optimal sizing of hybrid renewable energy systems.

Consequently, a substantial body of literature has emerged addressing the optimal sizing and configuration of hybrid wind and solar power plants using a variety of optimization approaches.

2.1 Optimization techniques for hybrid wind and solar systems

A significant portion of the literature focuses on the application of mathematical optimization techniques to determine the optimal sizing of hybrid renewable systems. Linear Programming - LP, mixed-integer linear programming - MILP, and related formulations are among the most widely adopted approaches due to their ability to incorporate multiple technical and operational constraints.

[12] applied a MILP framework to optimize the sizing of a hybrid wind and photovoltaic system in industrial applications, explicitly considering load profiles, site constraints, and operational costs. Similarly, [11] proposed a MILP model for the design of isolated rural hybrid microgrids in Peru, aiming to minimize investment costs while ensuring adequate energy supply. [19] developed a MILP based planning model for grid connected hybrid systems with energy storage, focusing on minimizing the net present cost of electricity generation.

Other studies have explored multi-objective and hierarchical optimization approaches. [6] introduced a multi-objective optimization model for hybrid renewable energy system design, balancing cost and reliability criteria. [25] proposed a bi-level planning framework that integrates capacity planning and operational optimization to maximize return on investment. These works demonstrate the effectiveness of mathematical programming techniques in identifying cost-efficient and technically viable configurations for hybrid wind and solar systems.

2.2 Economic viability and decision-support approaches

Beyond technical optimization, several studies emphasize the economic viability of hybrid systems and their role as decision-support tools for planners and investors. These approaches typically focus on metrics such as levelized cost of energy - LCOE, lifecycle costs, and comparative assessments between hybrid and standalone configurations.

[3] presented a decision-aid methodology to evaluate the feasibility of hybridizing existing wind power plants with photovoltaic generation and energy storage. Their results highlighted improvements in infrastructure utilization and capacity factors when hybrid solutions are adopted. [26] investigated the robust operation of hybrid wind and solar systems with battery storage under electricity price uncertainty, revealing trade-offs between short-term revenue optimization and long-term system performance.

Other works, such as [17, 27], applied optimization techniques based on lifecycle cost minimization and bio-inspired algorithms, respectively, to determine optimal component sizing for hybrid systems in isolated or rural contexts. Collectively, these studies reinforce the economic advantages of hybrid renewable energy systems when properly sized and optimized.

2.3 Resource complementarity and planning perspectives

Another important research stream investigates the complementarity between renewable energy resources, particularly wind and solar, from a planning and system integration perspective. Resource complementarity is often assessed through statistical correlation analyses, geographic evaluations, or scenario-based planning studies.

[28] analyzed the local complementarity between wind and solar photovoltaic resources in Portugal, demonstrating that hybridization can reduce curtailment and increase renewable energy penetration. In a complementary study, [3] explored different planning scenarios comparing hybrid and isolated deployment strategies, showing that coordinated resource integration can enhance overall system efficiency. [10] proposed a quantitative method to evaluate wind, solar and hydro complementarity and optimize generation ratios in large-scale systems.

These studies clearly show that resource complementarity can provide operational and planning benefits. However, in most cases, complementarity is evaluated as an external indicator or planning guideline rather than being directly embedded within the mathematical formulation of the sizing problem.

2.4 Synthesis and research gap

Despite the extensive literature on the optimal sizing of hybrid wind and solar renewable energy systems, a notable gap remains. Most existing studies do not explicitly incorporate the temporal complementarity between wind and solar resources into the optimization model itself. While several works acknowledge resource complementarity from a statistical, geographic, or planning perspective, this characteristic is rarely introduced as a structural constraint within the sizing formulation.

Instead, most optimization models prioritize minimizing costs, maximizing energy production, or improving reliability, implicitly assuming independent or average resource behavior. As a result, the potential benefits of temporal anti-correlation, particularly regarding improved grid utilization and reduced infrastructure idleness, are not fully captured. This limitation is especially relevant in regions where wind and solar generation profiles are strongly anti-correlated, such as in many areas of Brazil.

Addressing this gap, the present study proposes an optimization model that explicitly integrates wind and solar temporal complementarity into the sizing process. By embedding resource complementarity directly into the linear programming formulation under grid capacity constraints, the proposed approach enables a more realistic and efficient representation of hybrid system behavior, thereby enhancing both economic performance and infrastructure utilization.

3. Proposed optimization model

This study introduces a practical and accessible methodology for determining the optimal sizing of hybrid photovoltaic and wind power plants, with a specific focus on grid integration constraints. While optimization of renewable energy systems is a well-established topic, most existing models primarily focus on minimizing lifecycle cost, net present cost, or levelized cost of energy, often under average resource assumptions [11-12, 19]. Several formulations incorporate land or load constraints; however, grid capacity limitations are frequently treated as static upper bounds on installed capacity rather than as effective simultaneous injection constraints [3, 20].

Moreover, although resource complementarity between wind and solar has been widely investigated from statistical and planning perspectives [10, 21], it is rarely embedded directly within linear programming sizing formulations as a structural constraint. In many cases, complementarity is assessed ex-post through correlation analysis, without influencing the optimization structure itself. Consequently, the potential gains in grid utilization and infrastructure efficiency associated with temporal anti-correlation remain underrepresented in practical sizing models.

The novelty of the present work lies in explicitly integrating complementarity grid constraints into a linear programming framework tailored for early-stage project development, thereby linking resource behavior and infrastructure limitations within a single decision-support model.

The proposed model is implemented in Microsoft Excel® using the Solver add-in, making it easy to apply, modify, and replicate. While several advanced optimization tools exist, such as HOMER [29-31], the proposed model was deliberately designed to lower the entry barrier for project developers and policymakers who may lack access to specialized software or programming expertise. This approach ensures transparency, accessibility, and customizability, especially in early-stage project evaluation or capacity expansion planning.

Figure 1 illustrates a typical constraint faced in real hybrid system design: the proportion of installed generation capacity versus the available transmission limit. Historically in Brazil, grid connection contracts required summing the full installed capacity of each energy source, without considering complementarity. Recent regulatory updates [32] now allow contracted capacity to reflect the effective power injected, unlocking new opportunities for hybrid system efficiency, which our model explicitly addresses

To validate the methodology, a real site was used as a case study, where wind and solar resources are co-located. The model compares the performance of stand-alone systems versus the hybrid configuration, showing how complementarity reduces the overall cost of energy and improves grid usage. The optimization model uses input data obtained from local measurements, including wind speed, solar irradiation, land availability, and grid restrictions, which are described in detail in Section 4.

3.1 Model overview

From the perspective of a decision-maker evaluating a site for renewable energy investment, the goal is to determine the optimal composition between solar, wind, or hybrid generation systems to minimize the overall cost of energy and reduce grid idleness, given site-specific characteristics, energy demand, and grid constraints.

Three main alternatives are analyzed:

- Option 1: Onshore wind power plant.
- Option 2: Photovoltaic (PV) power plant.
- Option 3: Hybrid PV-Wind power plant, exploring resource complementarity.

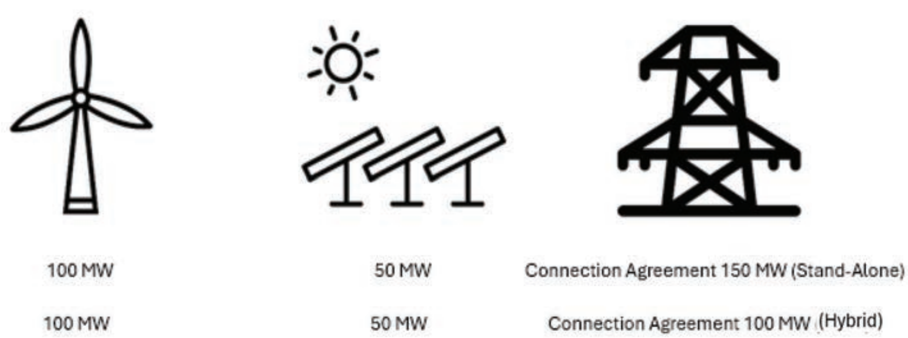

Figure 1: Schematic representation of wind and photovoltaic installed capacities relative to grid connection limits for Sento Sé, Bahia State, Brazil.

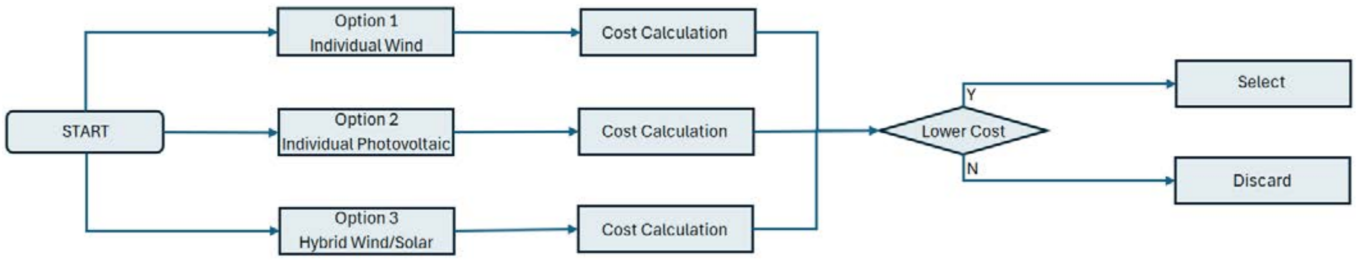

Figure 2: Decision-making framework for selecting the optimal configuration between wind, photovoltaic, and hybrid systems under site-specific resource and grid constraints.

This decision-making process is schematized in Figure 2.

As data for the model, it includes the characteristics of the site location and constraints that the model must consider, which are translated into specific inequalities. The characteristics and constraints are indicated in Figure 3.

3.2 Energy source characterization

This section presents the characterization of the renewable energy sources considered in the proposed optimization model. The objective is to define the main physical and operational parameters used to estimate energy production from photovoltaic and wind systems. For each source, the underlying generation principles and the mathematical formulations adopted in the model are described.

3.2.1 Photovoltaic generation:

The Sun is the primary source of energy for the Earth. The Earth's surface receives enormous amounts of solar energy in the form of light and heat. The Sun's energy can be used to produce electricity through the photovoltaic effect, which consists of the direct conversion of sunlight into electrical energy [33].

Photovoltaic generation is estimated to use solar irradiance, ambient temperature, module efficiency, and packing factor. The energy generated from the photovoltaic generator is given by the equation (1):

$$Epv = A \cdot n \cdot Pf \cdot I \cdot \Delta t \quad (1)$$

Where Epv is energy generated from the photovoltaic generator, A is the total area of the photovoltaic generator (m²), n is the generator efficiency, Pf is the packing factor, I is the hourly irradiance (kWh/m²) and Δt is the time interval (s).

3.2.2 Wind energy

The extraction of kinetic energy from the wind carried out wind turbines generators. To harness wind energy, the kinetic energy of the wind is converted into mechanical energy to perform work or convert it into electrical energy [34].

Wind generation is estimated using the wind speed, air density, and rotor swept area.

The energy generated by the wind turbine generator is given by the equation (2):

$$Ew = (\tfrac{1}{2} \cdot \rho \cdot A \cdot V^3) \,.\, \Delta t \quad (2)$$

Where Ew is the energy generated by the wind turbine, A is the swept area of the wind turbine (m²), ρ is the air density and (kg/m³) V is the wind speed (m/s) and Δt is the time interval (s) [34].

3.3 Decision variables

The decision variables are defined as:

Xpv = Installed photovoltaic capacity (MW)
Xw = Installed wind capacity (MW)

Both variables are continuous and non-negative.

3.4 Parameters

All parameters used in the formulation are explicitly defined in Table 1.

The complementarity coefficient γ presents the degree of temporal anti-correlation between wind and solar production. It adjusts the effective simultaneous injection into the grid.

3.5 Objective function and constraints

This section presents the objective function of the optimization model, which defines the decision-making criterion used to determine the optimal configuration of the hybrid system. The formulation aims to capture the main economic drivers associated with the deployment of wind and photovoltaic generation technologies, considering both investment and operational costs. By minimizing the total annualized cost of the system, the model identifies the most cost-effective combination of installed capacities while satisfying all technical and operational constraints described in the previous sections.

3.5.1 Objective function

The objective is to minimize the total annualized cost of the hybrid system:

$$\text{Minimize } Z = Cpvann \cdot Xpv + Cwann \cdot Xw$$

A set of constraints is introduced into the optimization model to capture the main technical and operational limitations of the system. These constraints ensure that the resulting solution is feasible with respect to land availability, energy supply requirements, and grid capacity restrictions. Furthermore, the formulation explicitly incorporates the temporal complementarity between wind and photovoltaic generation, enabling a more realistic representation of simultaneous power injection into the grid. The constraints are organized into four main groups: land availability, energy balance, grid capacity with complementarity, and non-negativity conditions for the decision variables.

Table 1: Algorithm parameters.

Symbol	Description	Unit
Xpv	Installed PV capacity	MW
Xw	Installed wind capacity	MW
Cpvann	Annualized cost of PV	USD/MW·year
Cwann	Annualized cost of wind	USD/MW·year
Apv	Land requirement per MW of PV	m²/MW
Aw	Land requirement per MW of wind	m²/MW
Amax	Total available land area	m²
CFpv	Capacity factor of PV	-
CFw	Capacity factor of wind	-
Lreq	Required average load	MW
GC	Grid capacity limit	MW
γ	Complementarity coefficient	-
αpv	PV coincidence-adjusted derived from hourly correlation analysis	-
αw	Wind coincidence-adjusted derived from hourly correlation analysis	-

3.5.2 Land availability constraint

The total area allocated to both technologies cannot exceed the available land.

$$Apv \cdot Xpv + Aw \cdot Xw \leq Amax$$

3.5.3 Energy supply constraint

To ensure that the required average load is met.

$$CFpv \cdot Xpv + CFw \cdot Xw \geq Lreq$$

3.5.4 Grid capacity constraints with complementarity

The effective simultaneous power injection into the grid must not exceed grid capacity limit.

$$Xpv + Xw - \gamma .min\,(Xpv, Xw) \leq GC$$

For linear implementation, this term is approximated using a linear complementarity factor

$$\alpha pv \cdot Xpv + \alpha w \cdot Xw \leq GC$$

where αi is defined as the ratio between effective coincident power and installed capacity for each technology.

This formulation replaces redundant individual grid constraints and ensures logical consistency.

To account for the temporal complementarity between wind and photovoltaic generation, the grid capacity constraint is formulated using coincidence-adjusted coefficients. Instead of assuming that both technologies reach their nominal installed capacity simultaneously, which would result in an overly conservative constraint, the model incorporates effective coincidence factors αpv and αw. These parameters represent the fraction of installed capacity that is expected to be simultaneously injected into the grid during critical operating periods, based on historical hourly generation profiles.

The relationship between the complementarity coefficient γ and the coincidence-adjusted coefficients (αpv, αw) is established through the concept of effective simultaneous generation. While γ provides an aggregate measure of the degree of anti-correlation between wind and solar resources, the coefficients αpv and αw translate this information into technology-specific factors suitable for linear optimization.

These coefficients are derived from the same hourly generation dataset used to compute γ, by estimating the fraction of installed capacity that contributes to simultaneous peak injection conditions. In this context, stronger complementarity (higher γ) leads to lower coincidence coefficients, reflecting reduced simultaneity between sources.

Therefore, αpv and αw can be interpreted as linearized representations of the complementarity effect, ensuring consistency between the statistical characterization of resource interaction and its incorporation into the grid constraint. This formulation replaces redundant individual grid constraints and ensures logical consistency while preserving model tractability.

It is important to note that the proposed formulation should be interpreted as a reduced-form planning model, rather than as a substitute for time-resolved operational simulations. The coincidence-adjusted coefficients (αpv, αw) are derived from historical hourly data and embedded into a static linear constraint to approximate effective simultaneous grid injection. This approach represents a deliberate trade-off between model accuracy and computational simplicity, aiming to provide a practical and transparent tool for early-stage project sizing. While a fully time-resolved formulation would capture complementarity endogenously, it would significantly increase model complexity and reduce accessibility for practitioners, which falls outside the intended scope of this study.

Despite its advantages in terms of simplicity and tractability, this approach involves some limitations. In particular, the static representation does not explicitly capture intra-day variability, extreme events, or temporal sequencing effects that may influence simultaneous generation patterns. Additionally, the accuracy of the approximation depends on the representativeness of the historical data used to derive the coincidence coefficients. Therefore, the proposed formulation is better suited for planning and pre-feasibility analysis, while more detailed time-resolved models may be required for operational studies and final system design.

In the case study, the coincidence-adjusted coefficients were derived consistently with the observed complementarity factor γ = 37%, calculated from the historical hourly generation profiles presented in Section 4.

3.5.5 Non-negativity constraints

$Xpv \geq 0$

$Xw \geq 0$

3.6 Model structure

The complete linear programming model is therefore:

$$Min\ Z = Cpvann \cdot Xpv + Cwann \cdot Xw$$

Subject to:

$$Apv \cdot Xpv + Aw \cdot Xw \leq Amax$$
$$CFpv \cdot Xpv + CFw \cdot Xw \geq Lreq$$
$$\alpha pv \cdot Xpv + \alpha w \cdot Xw \leq GC$$
$$Xpv \geq 0$$
$$Xw \geq 0$$

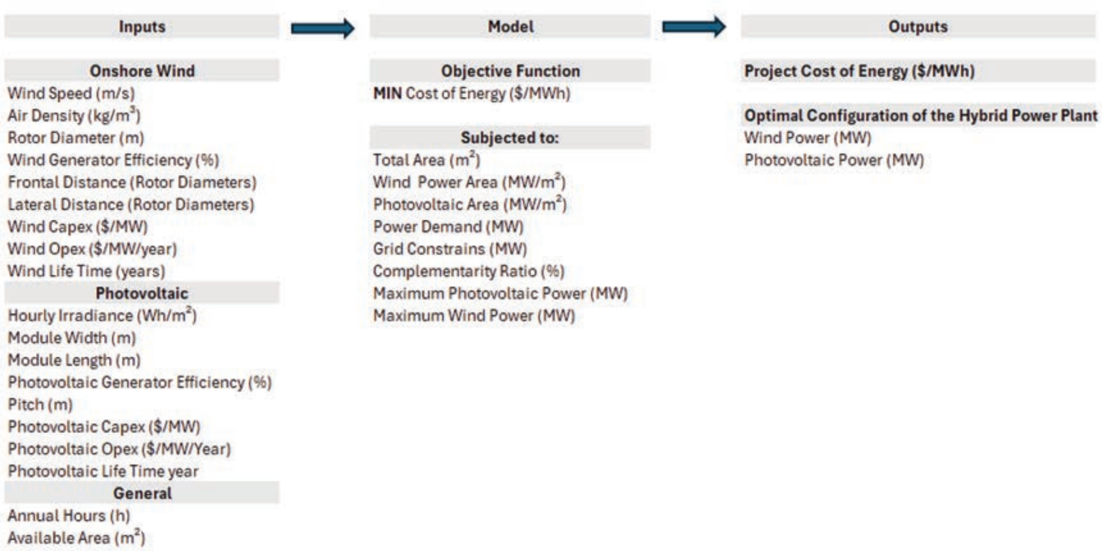

Figure 3: Schematic representation of the proposed optimization model, including input parameters, constraints, and decision variables.

The optimization is static and annual, using annual capacity factors and coincidence coefficients derived from hourly historical data.

It is necessary to clarify that the proposed algorithm can and should include additional variables and constraints in specific cases where they are relevant.

The data required for conducting the case study were obtained from local measurements and public sources, not limited to these, made available by regulatory and Brazilian sectoral entities, such as the National Electric Energy Agency - ANEEL, Grid Operator - ONS, and Energy Research Company - EPE.

For a better understanding of the formulation tool, a schematic representation is presented (Figure 3).

4. Case study in a Brazilian municipality

For this case study application, the municipality of Sento Sé in Bahia, Brazil was selected due to its exceptional characteristics for combined solar and wind sources. This choice is justified by the region's remarkable natural resource complementarity: characterized by intense solar irradiation during daylight hours and consistent wind speeds during nighttime periods (Figure 4).

A real-world site was used to demonstrate the application of the model. Local input data included:

- Measured solar irradiation and wind speed series.
- Regulatory limits (area, grid connection).
- CapEx (Capital Expenditure) and OpEx (Operational Expenditure) assumptions based on public Brazilian sources (ANEEL, ONS, EPE).

The objective was to compare the cost performance of pure photovoltaic, pure wind, and hybrid systems, emphasizing the economic and operational benefit of complementarities.

When evaluating the optimal sizing and source allocation in hybrid renewable energy systems, one of the key factors is the complementarity ratio between wind and solar resources in the region under evaluation. This study proposes a method aimed at minimizing the overall cost of energy and applies it to a location with suitable resource characteristics. Although in many regions around the world wind and solar sources exhibit low or no complementarity, the selected area (Sento Sé, in the state of Bahia, Brazil) presents a strong anti-correlation between wind and solar availability. This distinctive feature makes it an ideal site to test and validate the proposed model.

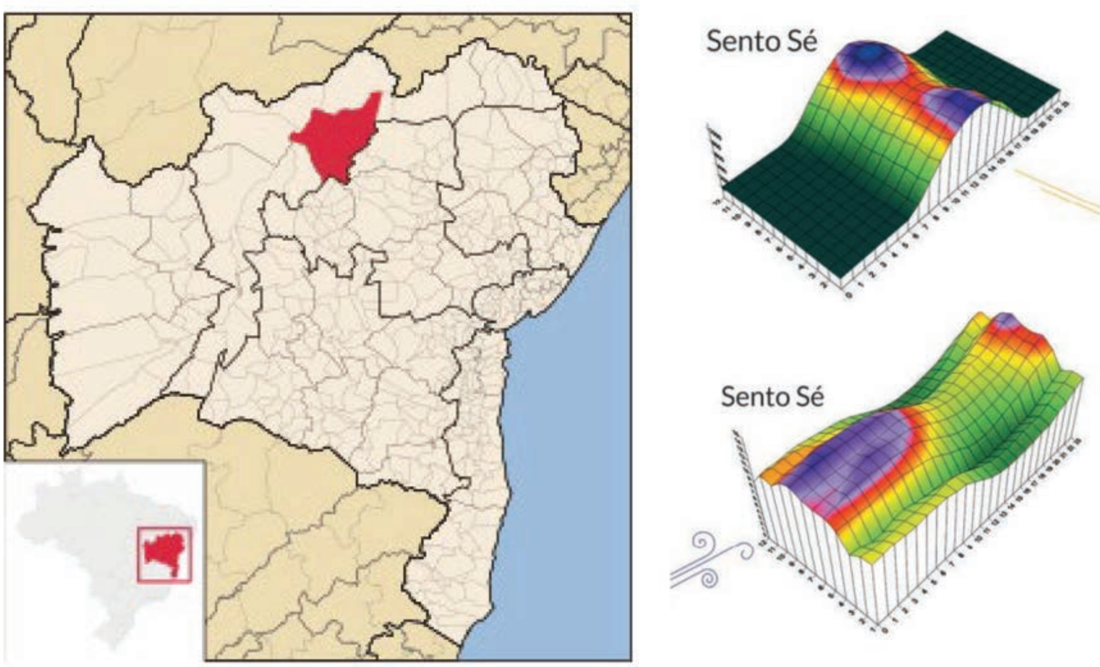

Figure 4: Location of Sento Sé, Bahia State, Brazil, and illustration of the complementary wind and solar resource patterns observed in the region.

All monetary values presented in this study are expressed in United States Dollars (USD).

4.1 Wind resource

The wind resource measured in the region and equipment characteristics selected to run the model were collected on site, assumed and calculated as indicated on Table 2.

4.2 Photovoltaic resource

The photovoltaic resource measured in the region and equipment characteristics selected to run the model were collected on site, assumed and calculated as indicated on Table 3.

4.3 Average daily resource profile (wind and solar)

The average daily resource profile is as indicated on Figure 5.

The annual average energy production is indicated in Figure 6.

The input data used in this study consists of full hourly time-series (8760 hours) of wind speed and solar irradiance obtained from local measurements. These time-series are used to derive key parameters such as capacity factors, generation profiles, and complementarity indicators. For visualization purposes, aggregated representations (e.g., average daily profiles) are presented in Figures 5 and 6; however, all statistical parameters used in the model are computed from the full-resolution dataset.

It is important to distinguish between two different definitions of maximum wind power used in this study. The value reported in Table 2 refers to the maximum installed (rated) capacity of the wind system, determined based on turbine specifications and spatial constraints. In contrast, the maximum wind power used in this section (Pw,max) is derived from the normalized hourly generation time series and represents the highest instantaneous value observed in the resource-based profile prior to scaling to installed capacity.

This distinction is necessary because the complementarity coefficient γ is computed based on the temporal interaction between wind and solar generation profiles, rather than on absolute installed capacities.

The structural complementarity between wind and solar resources was quantified using the coincidence-based indicator derived from their hourly power generation profiles. The complementary coefficient ***γ** is defined as:*

$$\gamma = 1 - (P\_hyb,max / (P\_w,max + P\_pv,max))$$

Where P hyb,max represents the maximum observed hybrid generation from both sources over the time series, and P_w,max and P_pv,max correspond to the

Table 2: Wind source data.

Variable	Unit	Value	Note
Wind Speed	m/s	10.22	Site collected
Air Density	kg/m³	1.25	Site collected
Rotor Diameter	m	150	Assumed
Wind Generator Efficiency	%	60%	Assumed
Wind Turbine Generator Swept Area	m²	17662	Calculated
Wind Turbine Power	MW	7.00	Calculated
Annual Hours	h	8760	Assumed
Available Areas	m²	20000000	Assumed
Front Distance	Diameters	6	Assumed
Lateral Distance	Diameters	3	Assumed
Area/MW	m²	14327	Calculated
No Wind Turbine Generator	Units	197	Calculated
Annual Energy	GWh	12195	Calculated
Installed Wind Capacity (Maximum Project Capacity)	GW	1.4	Calculated
CapEx	M USD/MW	0.9	Assumed
OpEx	USD/MW·year	54000	Assumed
Lifetime	Years	20	Assumed

maximum individual generation levels of wind and photovoltaic systems, respectively.

This formulation captures the degree of temporal anti-correlation between the resources. When both sources tend to generate simultaneously, the ratio P_ hyb,max / (P_w,max + P_pv,max) approaches unity, resulting in low values of γ. Conversely, when generation occurs at different times (i.e., strong complementarity), the simultaneous peak is significantly lower than the sum of individual peaks, leading to higher γ values.

In the case study, the maximum wind power observed was 2.56 GW, while the maximum photovoltaic power reached 1.68 GW, resulting in a theoretical combined maximum of 4.27 GW. However, the maximum simultaneous hourly generation observed in the dataset was 2.68 GW. Therefore, the complementarity coefficient is calculated as:

$$\boldsymbol{\gamma = 1 - (2}.68 / 4.27) = 0.37\ (37\%)$$

This value indicates a significant degree of temporal complementarity between wind and solar resources in the analyzed region.

The same hourly dataset is used to derive the coincidence-adjusted coefficients (αpv, αw), which represent the fraction of installed capacity effectively contributing to simultaneous grid injection under critical conditions. These coefficients ensure consistency between the statistical characterization of complementarity and its representation within the optimization model, as described in Section 3.6.3.

4.4 Option analysis and results discussion

This case study evaluates the technical and resource constraints presented in Tables 1 and 2 to meet an average load of 600 MW, subject to a grid capacity limit of 1.500 GW. Three scenarios were analyzed:

- Option 1: Onshore wind power only
- Option 2: Photovoltaic power only
- Option 3: A hybrid system combining wind and solar sources, considering a resource complementarity of 37%

The cost of energy results for each scenario is as follows:

a) Option 1 – Onshore wind power only:

The total annualized system cost is 237.6 M USD fully meeting the energy demand of 600 MW. The grid infrastructure utilization rate in this scenario is 64%.

b) Option 2 – Photovoltaic power only:

The algorithm returned an error for this configuration, as the maximum achievable capacity using a standalone photovoltaic solution was insufficient to meet the demand, primarily due to land use limitations.

c) Option 3 – Hybrid wind/solar system

The total annualized system cost is 161.6 M USD, with the energy demand fully covered of 600MW

Table 3: Solar source data.

Variable	Unit	Value	Note
Hourly Irradiance	Wh/m²	257	Site collected
Module Width	m	1.20	Assumed
Module Length	m	2.00	Assumed
Photovoltaic Module Area	m²	2.40	Assumed
Solar Generator Efficiency	%	20	Assumed
Annual Hours	h	8760	Assumed
Available Areas	m²	20000000	Assumed
Pitch	m	2	Assumed
No Photovoltaic Modules	Million units	4.16	Calculated
Photovoltaic Modules Area	m²	9997603	Calculated
Annual Energy	GWh	4496	Calculated
Total Solar Power	MW	513	Calculated
Area	m²/MW	38967	Assumed
CapEx	M USD/MW	0.8	Assumed
OpEx	USD/MW·year	20000	Assumed
Lifetime	Years	20	Assumed

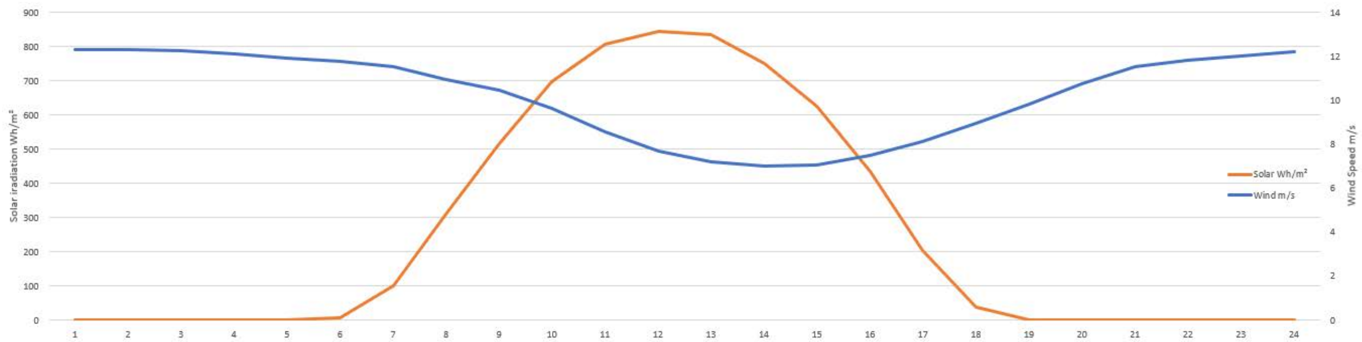

Figure 5: Average daily wind speed and solar irradiance profiles for Sento Sé, Bahia State, Brazil. Values represent hourly averages over one year. Solar irradiance is measured on a horizontal plane, and wind speed at hub height.

(463MW wind and 137MW Photovoltaic). The grid infrastructure utilization rate in this scenario is 84%.

Initially, the model was tested without incorporating complementarity conditions, evaluating only standalone wind and solar solutions. In this setup, the model proposed an onshore wind solution to meet the load, despite wind not being the lowest-cost source. This result was primarily due to the photovoltaic system's inability to meet demand constraints caused by limited available area.

However, once complementarity conditions between wind and solar were introduced, the algorithm recommended a hybrid configuration. This resulted in a 32% reduction in the cost of energy compared to the wind standalone solution.

Beyond the cost advantage, the hybrid system also led to more effective use of the grid infrastructure. In this specific case study, when comparing the standalone wind system to the hybrid wind-solar configuration, grid utilization improved by approximately 20%, highlighting an additional operational benefit of resource complementarity in hybrid power plants.

It is important to note that the results obtained in this case study correspond to a region with a high degree of wind-solar complementarity (γ = 37%), which represents a favorable scenario for hybrid system performance. In regions with moderate or low complementarity, the simultaneous generation of wind and solar tends to be higher, resulting in increased coincidence factors (αpv, αw) and, consequently, more restrictive grid capacity constraints.

Under such conditions, the economic and operational benefits of hybridization may be reduced, and the optimal solution may shift toward configurations dominated by a single technology. Nevertheless, the proposed model remains fully applicable, as it systematically

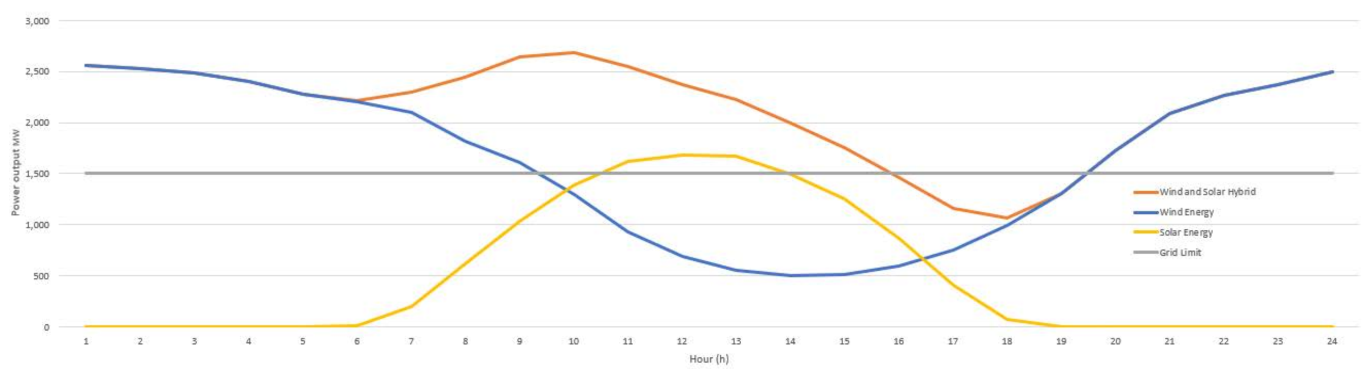

Figure 6: Average annual power generation profiles for wind and photovoltaic systems in Sento Sé, Bahia State, Brazil, derived from historical resource data.

Table 4: Summary of optimization results by scenario.

Scenario	Wind Capacity (MW)	PV Capacity (MW)	Total Installed Capacity (MW)	Total Lifecycle Cost (M USD)	Cost Reduction vs Wind Only	Grid Utilization (%)	Feasible Solution
Option 1 – Onshore Wind Only	600	0	600	237.6	–	64%	Yes
Option 2 – PV Only	0	≤513.25 (max land limit)	Not feasible	Not feasible	–	–	No (Land Constraint)
Option 3 – Hybrid Wind-Solar	463	137	600	161.6	32%	84%	Yes

captures these effects and adapts the optimal sizing to the local resource characteristics and infrastructure limitations. Therefore, the results presented in this study can be interpreted as an upper-bound estimate of the potential gains achievable through resource complementarity.

The application of this model in Sento Sé, Bahia, Brazil, a region characterized by a strong anti-correlation between wind and solar availability, yielded significant results. The analysis demonstrated that a hybrid wind-solar power plant configuration achieved a substantial reduction in the overall cost of energy compared to a wind-only solution capable of meeting the same energy demand. Furthermore, the hybrid system led to a notable increase in grid infrastructure utilization, highlighting the potential for more efficient use of existing transmission and distribution networks. The standalone photovoltaic system, in contrast, was unable to meet the energy demand due to land use limitations, underscoring the value of a combined approach in overcoming individual resource constraints.

5. Managerial implications

The findings of this study offer practical insights for project developers, investors, and policymakers involved in the planning and implementation of renewable energy projects. The proposed linear programming model, by incorporating constraints such as land availability, grid capacity, and resource complementarity, serves as an accessible decision-support tool, particularly during the early stages of project development.

From a managerial perspective, the model enables reasoned decisions regarding the optimal configuration of hybrid power plants by the anti-correlation between wind and solar resources, the approach allows for a reduction in energy production costs within the constraints of existing infrastructure.

The model implementation in Excel, using the Solver add-in, also ensures adoption by those without access to specialized optimization software or advanced programming knowledge. Managers can simulate different scenarios, assess trade-offs between cost, land use, and infrastructure, and identify configurations that result in both technical and economic feasibility.

Additionally, the model adds strategic value in regulatory environments as hybrid projects become more common and regulations evolve to allow connection agreements based on energy spill rather than solely on installed capacity.

For power sector managers and planners, the model serves as a replicable methodology to guide the expansion of installed generation capacity and optimize the use of existing transmission infrastructure.

In summary, this study promotes an optimized approach to hybrid system planning, fostering energy transitions that are cost-effective, efficient, and sustainable.

6. Conclusions

This study presented an optimization model sizing of hybrid wind and solar renewable power plants, directly addressing the growing need for efficient integration of renewable energy sources. The core novelty of this research lies in its explicit incorporation of systemic grid constraints and the benefits of resource complementarity (anti-correlation) into the optimization process, a factor often overlooked in traditional sizing models.

These findings support the proposition that hybrid power plants, strategically designed to leverage the complementary nature of wind and solar resources, offer a compelling pathway towards achieving both lower energy costs and enhanced grid efficiency. By moving beyond optimization based solely on energy production or cost metrics, this methodology provides a practical tool for developers and decision-makers. The implementation of the linear programming model in Microsoft Excel using the Solver add-in further enhances its accessibility and potential for widespread adoption, especially in early-stage project evaluation and capacity expansion planning where specialized software might not be readily available.

The outcome of the case study in a region with high resource anti-correlation underscores the importance of considering site-specific resource characteristics in the design of renewable energy systems. The model's ability to integrate technical aspects (resource availability, land constraints), economic parameters (CapEx, OpEx), and regulatory limitations (grid capacity) into a single optimization framework makes it a valuable asset for informed decision-making in the renewable energy sector.

The main contributions of this study, particularly for early-stage project evaluation and capacity expansion planning, are threefold: it proposes a novel modeling approach that incorporates grid constraints and the complementarity between wind and solar resources into the sizing process; it offers an accessible implementation that facilitates its use by developers and researchers without the need for advanced optimization software; and it presents a real-world case study that demonstrates the practical applicability and the performance gains achieved through the proposed methodology.

Nevertheless, it is important to acknowledge that the proposed model adopts a simplified representation of temporal complementarity through aggregated parameters. While this enables practical application and computational efficiency, it does not fully capture chronological variability, extreme operating conditions, or temporal sequencing effects. Therefore, the model is more suitable for planning and early-stage decision-making, whereas more detailed time-resolved approaches may be required for operational analysis and final system design.

Furthermore, although the case study focuses on a region with high wind-solar complementarity, the proposed model is general and can be applied to locations with varying degrees of resource correlation. In scenarios with lower complementarity, the benefits of hybridization tend to decrease due to higher simultaneity of generation and more binding grid constraints. However, the model remains effective in identifying the optimal configuration under such conditions, reinforcing its applicability as a decision-support tool across diverse geographical contexts.

It is important to highlight that a detailed sensitivity analysis of key input parameters, such as capital and operational expenditures (CapEx/OpEx), complementarity level (γ), land availability, and demand, was not explicitly addressed in this study. Incorporating such analysis would provide further insights into the robustness of the optimal solutions under varying economic and resource conditions.

Based on this study insights, future research could further enhance the applicability of the proposed approach by incorporating sensitivity analyses of key input parameters, as well as time-resolved constraints, stochastic representation of resource variability, and energy storage systems to improve flexibility, reliability, and grid stability. Additionally, exploring the methodology's effectiveness across different geographical regions with varying degrees of wind and solar resource complementarity and diverse grid infrastructure conditions would further validate its robustness and broad applicability. Ultimately, this research contributes to the growing body of knowledge on hybrid renewable energy systems and offers a tangible approach to support the global energy transition towards a more sustainable and efficient energy future.

References

[1] Hassan, Q., Viktor, P., Al-Musawi, T. J., Ali, B. M., Algburi, S., Alzoubi, H. M., ... & Jaszczur, M. (2024). The renewable energy role in the global energy Transformations. Renewable Energy Focus, 48, 100545. https://doi.org/10.1016/j.ref.2024.100545

[2] Klyve, Ø. S., Olkkonen, V., Nygård, M. M., Lingfors, D., Marstein, E. S., & Lindberg, O. (2025). Retrofitting wind power plants into hybrid PV–wind power plants: Impact of resource related characteristics on techno-economic feasibility. *Applied Energy*, *379*, 124895. https://doi.org/10.1016/j.apenergy.2024.124895

[3] Silva, A. R., & Estanqueiro, A. (2022). From wind to hybrid: A contribution to the optimal design of utility-scale hybrid power plants.*Energies*, *15*(7), 2560. https://doi.org/10.3390/en15072560

[4] Sadeghibakhtiar, E., Naeimi, A., Naderi, S., Pignatta, G., & Behbahaninia, A. (2024). Size optimization of a stand-alone solar-wind-battery hybrid system for net zero energy buildings: A case study. *Energy and Buildings*, *313*, 114204. https://doi.org/10.1016/j.enbuild.2024.114204

[5] Wang, S., Jia, R., Shi, X., Luo, C., An, Y., Huang, Q., ... & Lei, X. (2022). Research on capacity allocation optimization of commercial virtual power plant (CVPP). *Energies*, *15*(4), 1303. https://doi.org/10.3390/en15041303

[6] Pereira, M. T., Rego, E. E., & Nagano, M. S. (2018). A multiobjective optimization model for the design of hybrid renewable energy systems. *IEEE Latin America Transactions*, *16*(12), 2925-2933. https://doi.org/10.1109/TLA.2018.8804258

[7] Abdelkader, A., Rabeh, A., Ali, D. M., & Mohamed, J. (2018). Multi-objective genetic algorithm based sizing optimization of a stand-alone wind/PV power supply system with enhanced battery/supercapacitor hybrid energy storage. *Energy*, *163*, 351-363. https://doi.org/10.1016/j.energy.2018.08.135

[8] Babaremu, K., Olumba, N., Chris-Okoro, I., Chuckwuma, K., Jen, T. C., Oladijo, O., & Akinlabi, E. (2022). Overview of solar–wind hybrid products: Prominent challenges and possible solutions. *Energies*, *15*(16), 6014. https://doi.org/10.3390/en15166014

[9] Roberts, J. J., Cassula, A. M., Silveira, J. L., da Costa Bortoni, E., & Mendiburu, A. Z. (2018). Robust multi-objective optimization of a renewable based hybrid power system. *Applied Energy*, *223*, 52-68. https://doi.org/10.1016/j.apenergy.2018.04.032

[10] Han, S., Zhang, L. N., Liu, Y. Q., Zhang, H., Yan, J., Li, L., ... & Wang, X. (2019). Quantitative evaluation method for the complementarity of wind–solar–hydro power and optimization of wind–solar ratio. *Applied energy*, *236*, 973-984. https://doi.org/10.1016/j.apenergy.2018.12.059

[11] Ferrer-Martí, L., Domenech, B., García-Villoria, A., & Pastor, R. (2013). A MILP model to design hybrid wind–photovoltaic isolated rural electrification projects in developing countries. *European Journal of Operational Research*, *226*(2), 293-300. https://doi.org/10.1016/j.ejor.2012.11.018

[12] Lamedica, R., Santini, E., Ruvio, A., Palagi, L., & Rossetta, I. (2018). A MILP methodology to optimize sizing of PV-Wind renewable energy systems. *Energy*, *165*, 385-398. https://doi.org/10.1016/j.energy.2018.09.087

[13] Duchaud, J. L., Notton, G., Fouilloy, A., & Voyant, C. (2019). Wind, solar and battery micro-grid optimal sizing in Tilos Island. *Energy Procedia*, *159*, 22-27. https://doi.org/10.1016/j.egypro.2018.12.012

[14] Cai, W., Li, X., Maleki, A., Pourfayaz, F., Rosen, M. A., Nazari, M. A., & Bui, D. T. (2020). Optimal sizing and location based on economic parameters for an off-grid application of a hybrid system with photovoltaic, battery and diesel technology. *Energy*, *201*, 117480. https://doi.org/10.1016/j.energy.2020.117480

[15] Yasmeen, R., & Shah, W. U. H. (2024). Energy uncertainty, geopolitical conflict, and militarization matters for renewable and non-renewable energy development: perspectives from G7 economies. *Energy*, *306*, 132480. https://doi.org/10.1016/j.energy.2024.132480

[16] Chakir, A., & Tabaa, M. (2024). Hybrid Renewable Production Scheduling for a PV–Wind-EV-Battery Architecture Using Sequential Quadratic Programming and Long Short-Term Memory–K-Nearest Neighbors Learning for Smart Buildings. Sustainability, 16(5), 2218. https://doi.org/10.3390/su16052218

[17] Ashok, S. (2007). Optimised model for community-based hybrid energy system. Renewable energy, 32(7), 1155-1164. https://doi.org/10.1016/j.renene.2006.04.008

[18] Kusakana, K., Vermaak, H. J., & Numbi, B. P. (2012, July). Optimal sizing of a hybrid renewable energy plant using linear programming. In *IEEE Power and Energy Society Conference and Exposition in Africa: Intelligent Grid Integration of Renewable Energy Resources (PowerAfrica)* **(pp. 1-5). IEEE.** https://doi.org/10.1109/PowerAfrica.2012.6498608

[19] Theo, W. L., Lim, J. S., Alwi, S. R. W., Rozali, N. E. M., Ho, W. S., & Abdul-Manan, Z. (2016). An MILP model for cost-optimal planning of an on-grid hybrid power system for an eco-industrial park. *Energy*, *116*, 1423-1441. https://doi.org/10.1016/j.energy.2016.05.043

[20] Morais, H., Kádár, P., Faria, P., Vale, Z. A., & Khodr, H. M. (2010). Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming. *Renewable Energy*, *35*(1), 151-156. https://doi.org/10.1016/j.renene.2009.02.031

[21] Couto, A., & Estanqueiro, A. (2020). Exploring wind and solar PV generation complementarity to meet electricity demand. *Energies*, *13*(16), 4132. https://doi.org/10.3390/en13164132

[22] Connolly, D., Lund, H., Mathiesen, B. V., & Leahy, M. (2010). A review of computer tools for analysing the integration of renewable energy into various energy systems. *Applied energy*, *87*(4), 1059-1082. https://doi.org/10.1016/j.apenergy.2009.09.026

[23] Lund, H., Østergaard, P. A., Connolly, D., Ridjan, I., Mathiesen, B. V., Hvelplund, F., ... & Sorknæs, P. (2016). Energy storage and smart energy systems. *International Journal of Sustainable Energy Planning and Management*, *11*, 3-14. https://doi.org/10.5278/ijsepm.2016.11.2

[24] Østergaard, P. A., Lund, H., Johannsen, R. M., Sperling, K., & Duic, N. (2024). Ten years of sustainable energy planning and management. *International Journal of Sustainable Energy Planning and Management*, *40*, 1-7. https://doi.org/10.54337/ijsepm.8360

[25] Yang, B., Guo, Y., Xiao, X., & Tian, P. (2020). Bi-level capacity planning of wind-PV-battery hybrid generation system considering return on investment. *Energies*, *13*(12), 3046. https://doi.org/10.3390/en13123046

[26] Bakhtvar, M., & Al-Hinai, A. (2021). Robust operation of hybrid solar–wind power plant with battery energy storage system. Energies, 14(13), 3781. https://doi.org/10.3390/en14133781

[27] Hatata, A. Y., Osman, G., & Aladl, M. M. (2018). An optimization method for sizing a solar/wind/battery hybrid power system based on the artificial immune system. *Sustainable energy technologies and assessments*, *27*, 83-93. https://doi.org/10.1016/j.seta.2018.03.002

[28] Couto, A., & Estanqueiro, A. (2021). Assessment of wind and solar PV local complementarity for the hybridization of the wind power plants installed in Portugal. *Journal of Cleaner Production*, *319*, 128728. https://doi.org/10.1016/j.jclepro.2021.128728

[29] Lambert, T., Gilman, P., & Lilienthal, P. (2006). Micropower system modeling with HOMER. Integration of alternative sources of energy, 1(1), 379-385. https://doi.org/10.1002/0471755621.ch15

[30] Energy Exemplar Pty Ltd. (2013). *PLEXOS® Integrated Energy Model*. Energy Exemplar Pty Ltd. https://www.energyexemplar.com/plexos

[31] Rosenthal, R.E., 2014. *GAMS – A User's Guide*. GAMS Development Corporation, Washington, DC, USA. Available at: GAMS User's Guide https://www.gams.com/latest/docs/UG_MAIN.html?utm_source=chatgpt.com

[32] Agência Nacional de Energia Elétrica (ANEEL). (2021). *Normative Resolution No. 954/2021.* https://www.aneel.gov.br

[33] Villalva, M.G., Gazoli, J.R., 2012. *Energia solar fotovoltaica: conceitos e aplicações*. Editora Érica, São Paulo, Brazil. ISBN: 978-85-365-1489-5.

[34] Custódio, R.S., 2013. *Wind Energy for Electric Power Generation*, 2nd ed. Synergia Editora, Rio de Janeiro, Brazil.