

Article

Quantifying the Capacity Credits of Intermittent Renewables: Implications for Power System Planning

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Abstract

The European Union's objective of climate neutrality by 2050 requires a profound transformation of national power systems. In Poland, this transition involves reducing coal-based generation and expanding variable renewable energy sources (VRES), particularly wind and solar. Between 2020 and 2025, onshore wind capacity increased from 5.9 GW to nearly 11 GW, and solar from 1.6 GW to over 22 GW, while peak electricity demand in 2024 exceeded 28 GW. Although VRES are essential for decarbonization, their variability poses challenges for system adequacy. This study assessed the adequacy contribution of onshore wind and solar power plants using capacity credit as a key indicator. Two approaches were applied: a deterministic Load Duration Curve (LDC) method and probabilistic methods—Effective Load Carrying Capability (ELCC) and Equivalent Firm Capacity (EFC)—based on historical data from 2021–2024. The results show that capacity credits for onshore wind ranged from 8.08% to 17.27%, and for solar from 1.82% to 6.60%, depending on the method and year. Despite the presence of 1.7 GW of pumped storage and 4.4 GW of battery storage contracted in the capacity market, the relatively low VRES capacity credits underline the continued need for flexible, dispatchable generation. The findings highlight the importance of accurate capacity credit estimation to guide investment in renewables, storage, and backup capacity, thereby supporting a secure and reliable energy transition in Poland.

Keywords: capacity credit; variable renewable energy sources; Polish power system; system adequacy; deterministic approach; probabilistic approach



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1. Introduction

The European Union's ambitious climate neutrality target for 2050, coupled with the interim goal of reducing greenhouse gas emissions by at least 55% by 2030, poses significant challenges across member states [1–3]. Poland, as one of the most coal-dependent countries in the EU, faces a particularly complex transition. Although the share of coal in electricity generation has steadily declined, it still accounted for 57.1% of total output in 2024, while renewables reached a record-high 29.6% [4]. Between 2020 and 2025, installed wind capacity grew from 5.9 GW to nearly 11 GW, and solar photovoltaics from 1.6 GW to more than 22 GW [5]. Meanwhile, peak demand exceeded 28 GW in 2024, underscoring the growing challenge of balancing supply and demand in a system with rapidly increasing shares of weather-dependent renewables.

Looking ahead, solar, onshore, and offshore wind are all expected to expand further. By 2030, solar capacity is projected to reach around 29 GW, rising to 46.3 GW by 2040, while onshore wind is expected to grow to approximately 19 GW by 2030 and 25.8 GW by 2040.

Offshore wind, anticipated to enter the Polish power system around 2026, is forecast to reach 5.9 GW by 2030 and expand significantly to 17.9 GW by 2040 [6]. These targets reflect Poland's commitments under the EU climate and energy framework, which requires the country to achieve a 32.6% share of renewables in gross final energy consumption by 2030 as part of the EU-wide renewable energy target. Long-term projections further suggest that this share could rise to 58.4% by 2040 [6].

In parallel, Poland plans to diversify its generation mix by commissioning nuclear power reactors beyond 2035, with a total capacity of 6–9 GW by 2045, while storage resources are expected to play a growing role in ensuring system flexibility. At present, storage is dominated by pumped hydro with a discharge capacity of 1.7 GW, complemented by 4.4 GW of battery-based storage already contracted through the capacity market. However, despite these ambitious plans, the Polish power system remains characterized by a coal-dominated generation mix, relatively low interconnection levels compared to its neighbors, and pronounced seasonal as well as diurnal variability in VRES output. Such structural features raise pressing adequacy risks that are not fully addressed in existing policy frameworks such as the KPEiK [6] or PEP2040 [7].

Although variable renewables are critical for reducing emissions, their intermittent nature poses significant reliability challenges [8]. Solar output is largely unavailable during winter evening peaks, while wind generation is subject to strong seasonal variability. High penetration of these resources increases the frequency of both surplus generation and supply shortfalls, particularly in a system with limited interconnections and still a high dependence on inflexible coal-fired units. These challenges highlight the importance of evaluating not only the environmental benefits of VRES but also their reliable contribution to adequacy during critical demand periods.

A widely used measure in this context is capacity credit (CC), which quantifies the dependable contribution of a resource to peak demand [9]. However, estimating this metric is complex, as results strongly depend on methodological choices and system-specific conditions. Two main methodological approaches are typically used for this purpose [10]. Deterministic (approximation-based) methods are widely applied in practice due to their low data requirements and computational simplicity. They often rely on historical average generation or typical output during peak hours, which makes them attractive for preliminary assessments or systems with limited data. This simplicity, however, comes at the cost of realism, as such methods neglect the stochastic and time-dependent interactions between VRES generation and demand, potentially leading to optimistic or biased estimates.

In contrast, probabilistic (reliability-based) methods explicitly capture the variability and uncertainty of both load and renewable output, often using Monte Carlo simulations or convolution techniques. These approaches require more detailed data and greater computational effort but provide a more robust and realistic assessment of system adequacy. As a result, they are increasingly adopted by transmission system operators and regulators, particularly for long-term planning in high-VRES scenarios. The choice between these methods depends on data availability, system-specific characteristics, and the analytical objectives of the study. This complexity is particularly acute in Poland, where rapid solar deployment, seasonal wind variability, and increasing evening peak demand coincide with limited cross-border balancing options. Against this backdrop, assessing the adequacy contribution of VRES requires a systematic comparison of alternative methodological approaches.

Numerous studies have examined capacity credit estimation methods, distinguishing between deterministic and probabilistic approaches. Jorgenson et al. [11], analyzing seven years of load and generation data, compared probabilistic and various deterministic methods and showed that approximation approaches can effectively capture the relationship between wind availability and system requirements, although the results are highly sensi-

tive to the chosen technique. Building on this, approximation-based method such as the Load Duration Curve (LDC) has been widely applied due to their relative simplicity and modest data requirements. Mills et al. [12], for instance, demonstrated the applicability of LDC to solar and storage systems in the U.S., showing good alignment with probabilistic results despite limited computational needs. Similarly, Madaeni et al. [13,14] used a capacity factor (CF)-based method to assess concentrating solar power (CSP) and photovoltaic systems, reporting capacity credits ranging from 45% to 95% depending on location, system design, and tracking capability. Extending this line of work, Mills et al. [15] showed that CF-based methods can provide reasonable estimates at low penetration levels of VRES but become increasingly inaccurate as shares rise, since they fail to capture the shifting nature of high-risk periods. Overall, while deterministic approaches are practical and often valuable in data-constrained contexts or early phases of capacity expansion planning, their results can be highly sensitive to methodological choices [16,17] and tend to overlook stochastic and time-dependent interactions between renewable generation and demand, which limits their reliability under conditions of rapid renewable expansion.

To overcome these limitations, probabilistic methods have gained increasing prominence. These methods explicitly capture the temporal dynamics of renewables by employing metrics such as Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), and Expected Unserved Energy (EUE). Commonly used probabilistic frameworks include Effective Load Carrying Capability (ELCC), Equivalent Firm Capacity (EFC), and Equivalent Conventional Capacity (ECC), each representing the amount of perfectly reliable capacity required to replicate the reliability contribution of a variable renewable energy source [18]. Studies consistently find that ELCC, EFC and ECC results converge, providing a robust foundation for adequacy evaluation [19]. A recent multi-regional analysis across the U.S. [20] demonstrated that the marginal capacity contribution of renewables declines as penetration levels increase, while approximations based on top net load hours can still provide reasonable estimates for planning purposes. In Spain, Sequential Monte Carlo Simulation has been used to quantify the effective contribution of solar and wind [21], whereas in Taiwan, non-sequential Monte Carlo Simulation highlighted the sensitivity of adequacy outcomes to changing generation mixes [22]. In China, recent advances include a multi-timescale assessment framework that integrates storage to capture seasonal dynamics [23], as well as statistical innovations to better reflect short-term weather-driven fluctuations [24]. Collectively, these studies underscore the global relevance of probabilistic modeling, while also demonstrating that adequacy outcomes are highly context-dependent—varying with system structure, renewable profiles, and flexibility options.

Within Europe, ENTSO-E [25] and national transmission system operators have also published adequacy assessments, confirming the importance of capacity credit evaluations at the regional level. For example, Swedish studies indicate that wind power contributes around 9% of firm availability during peak load periods [26], while Danish analyses apply LOLE-based indicators to quantify the effective contribution of wind and solar [27]. Such findings provide useful benchmarks and highlight the diversity of methodological practices across European systems, reinforcing their relevance for the Polish case.

Despite this extensive body of literature, important gaps remain. Much of the existing research has focused on North American and Western European systems with higher interconnection capacities, more diversified generation mixes, and longer experience with large-scale renewables. By contrast, the Polish power system is distinguished by its coal-dominated mix, rapidly expanding yet relatively recent solar deployment, and a strongly seasonal wind profile—all combined with limited cross-border balancing options. Moreover, while the Polish capacity market assigns standardized availability coefficients to wind and solar, these values have not been systematically validated against alternative adequacy

methods. This lack of validation leaves uncertainty about how well official parameters reflect the actual contribution of VRES to system reliability under evolving conditions.

The objective of this study is to validate and compare selected deterministic and probabilistic methods (LDC, ELCC, and EFC) in estimating the capacity credit of wind and solar generation. The contribution of this work lies in systematically testing and benchmarking these approaches under the specific structural and operational conditions of the Polish power system. This methodological focus provides new insights into how different approaches influence adequacy outcomes, particularly in systems undergoing rapid structural transformation and increasing shares of variable renewables. A further innovative aspect of the study is the benchmarking of results against standardized capacity values published within the Polish capacity market. This comparison provides a practical reference point that enhances both the credibility and the policy relevance of the findings, linking academic methods with real-world adequacy planning. Overall, the study advances methodological understanding while delivering system-specific evidence directly relevant for researchers, regulators, and policymakers engaged in adequacy assessments and long-term power sector planning.

The subsequent sections are organized as follows. Section 2 describes the applied methods, summarized in a dedicated diagram and outlines the input data used in the analysis. Section 3 presents the key results, which are further comprehensively discussed in Section 4. Finally, Section 5 concludes the study by summarizing the main findings and contributions, while also identifying promising directions for further research.

2. Materials and Methods

Determining the capacity credit of variable renewable energy sources such as wind and solar is essential for assessing their contribution to power system adequacy. Because their output is strongly weather-dependent and time-varying, the estimation becomes methodologically challenging, particularly when generation does not coincide with peak demand. Capacity credit represents the dependable share of a unit's installed capacity under stressed system conditions. To address this challenge, the study applies two complementary approaches: a deterministic method based on the LDC and probabilistic methods, ELCC and EFC. The LDC method is relatively simple and requires limited data, but it may not fully capture variability and uncertainty. In contrast, ELCC and EFC provide a more comprehensive, reliability-based assessment. Applying the same input data across all methods enables a direct comparison of outcomes and a clearer understanding of how methodological choices affect the estimated capacity credit (throughout, “wind” refers to onshore wind).

2.1. Data

In both approaches, the capacity credit for wind and solar power plants was determined for 2021–2024. The analysis relied on publicly available datasets from the Polish transmission system operator (PSE), including hourly national electricity demand [28] and wind and solar generation [29]. All inputs were used at hourly resolution to ensure temporal consistency. Following changes in PSE's publication practices on 14 June 2024 (introduction of 15 min granularity pursuant to Regulation (EU) 2017/2195 (EBGL) [30]), quarter-hourly data were aggregated to hourly values [31]. While such aggregation may smooth out short-term fluctuations, adequacy assessments are conventionally performed at hourly resolution, so the potential impact on the results is expected to be limited. This ensured consistent coverage of the full 2021–2024 period while retaining the temporal resolution required by the applied methods. To further ensure data quality, potential outliers were cross-checked against original sources, and no smoothing was applied to preserve the

inherent variability essential for adequacy assessment. The resulting dataset was used as a harmonized input for both the LDC analysis and the ELCC/EFC calculations.

In addition, historical capacity factor profiles from the ENTSO-E Transparency Platform [32] were employed, primarily for the probabilistic analysis. These included hourly solar data for 1982–2021 and wind data for 2014–2023. The extended series supported representative distributions of meteorological conditions and were harmonized to the hourly structure of the 2021–2024 analysis, thus improving the robustness of ELCC and EFC results. This dual dataset design ensured that the applied methods were tested on both short-term operational data and long-term climatic variability, thereby strengthening the robustness of the results.

2.2. LDC Method

The LDC method, applied within the deterministic approach, estimates the capacity credit of wind and solar power plants by analyzing both the standard LDC and the Net LDC. The LDC ranks system demand in descending order over a given period (typically 1 year at hourly resolution), whereas the Net LDC reflects residual demand after subtracting the output of non-dispatchable renewables. Net load is the portion of demand that must be met by dispatchable generation and serves as a key indicator of adequacy. In the Net LDC, hourly residual demand values are sorted independently of the original load sequence, which enables the method to capture shifts in the timing of critical hours caused by renewable generation.

The method quantifies how renewables reduce the system demand that must be met by dispatchable capacity during the most critical hours. Capacity credit is calculated as the difference between the area under the LDC and the Net LDC over a predefined number of peak hours. These hours represent periods of highest risk of supply shortage due to elevated demand or limited dispatchable capacity. Following common practice [12] and its use in capacity expansion models such as NREL's ReEDS [10,11,33,34] and RPM [35], the top 100 h of highest system demand ($\approx 1.1\%$ of the year) were selected in this study. This choice captures the most critical stress periods while maintaining a reasonable computational effort. Prior studies show that 100 h provides a close approximation to reliability-based metrics and that moderate changes to the threshold have only limited impact on results. Figure 1 illustrates the principle of the LDC-based calculation.

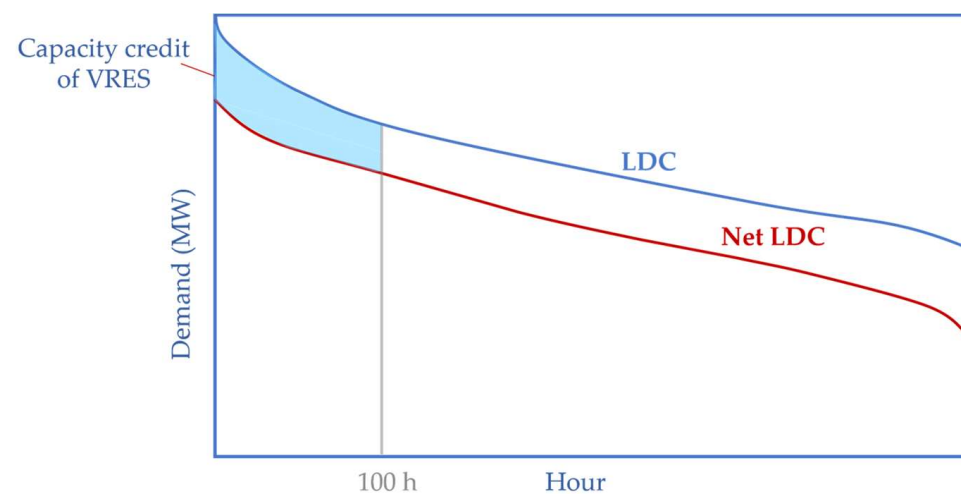


Figure 1. Visualization of the capacity credit calculation based on the LDC method. Source: Own elaboration based on [10].

The difference in area is then divided by the installed capacity of the analyzed renewable technology and the number of selected peak hours to obtain a fractional capacity credit, which is subsequently expressed as a percentage. Equations (1) and (2) present the calculation for aggregated and hourly formulations, respectively.

$$CC = \frac{LDC - \text{NetLDC}}{\text{Capacity} \times \text{PeakHours}} \times 100 \quad (1)$$

$$CC = \frac{LDC - \text{NetLDC}}{\text{Capacity}} \times 100 \quad (2)$$

where

CC—capacity credit [%];

LDC—area under the Load Duration Curve over the selected peak hours [MWh] in Equation (1), or load value during a given hour [MW] in Equation (2);

Net LDC—area under the Net Load Duration Curve over the selected peak hours [MWh] in Equation (1), or net load value during a given hour [MW] in Equation (2);

Capacity—installed capacity of the analyzed renewable technology (e.g., wind or solar) [MW];

Peak Hours—number of hours selected as the system's peak demand period [h];

$\times 100$ —operation used to express the result as a percentage.

This shows how renewable generation reduces the frequency and severity of peak demand hours, effectively lowering residual demand during critical periods. Because the LDC and Net LDC are independently sorted, the gap between them reflects the overall reduction in net peak load regardless of when the peaks occur. Thus, the method provides clear and intuitive insights into how variable renewables reshape both the magnitude and timing of critical hours, reducing reliance on firm dispatchable capacity in systems with growing shares of weather-dependent generation.

2.3. ELCC and EFC Method

The ELCC and EFC methods were applied within the probabilistic approach to estimate the capacity credit of wind and solar power plants. ELCC defines capacity credit as the additional load that can be reliably added to the system following the integration of a new generation unit—such as wind or solar—without reducing the original reliability level. In contrast, EFC defines the perfectly reliable firm capacity that provides the same adequacy contribution as the variable unit. Both methods jointly consider the temporal behavior of demand and renewable output, enabling a more realistic adequacy assessment than deterministic approximations.

Unlike the deterministic LDC method, ELCC and EFC rely on probabilistic reliability metrics. In this study, LOLE was adopted as the primary measure of reliability. LOLE quantifies the expected number of hours in a given year (typically 8760 h) during which available generation is insufficient to meet system demand. It is calculated as the sum of probabilities that generation falls short of demand in each hour, as shown in Equation (3):

$$\text{LOLE} = \sum_{t=1}^T p(G_t < D_t) \quad (3)$$

where

LOLE—Loss of Load Expectation [h];

t—hourly time-step index;

T—total number of hours in the analyzed period (typically $T = 8760$);

G_t —available generation capacity in hour t [MW];

D_t —system demand in hour t [MW];

$p(G_t < D_t)$ —probability that available generation is lower than demand in hour t .

Using LOLE as a common reference metric ensured a consistent and comparable assessment of the adequacy contribution of VRES. In this study, the reference value was set in line with adequacy standards commonly applied in Poland, corresponding to 3 h per year. This choice keeps the ELCC and EFC results consistent with national adequacy practices, while also enabling comparison with international benchmarks. For example, the widely used “1-day-in-10-years” criterion in North America corresponds to about 2.4 h per year, whereas in Europe adequacy targets vary: Ireland applies 8 h and Italy 3 h [36]. To further illustrate the logic of the procedures, LOLE values of 4 h and 8 h were also used in the methodological description and diagram, as these fall within the European range and highlight the flexibility of the methods across different national contexts.

Both methods began with synthetic hourly time series of available dispatchable generation capacity. These were obtained by combining the installed capacities (CAP) of coal, lignite and gas with assumed annual availability factors (AFA). The AFA values, generally in the range of 85–95% depending on technology, were chosen to represent forced outage conditions and to implicitly account for scheduled maintenance. Detailed unit-level data, including installed capacities and AFA assumptions are provided in Table A1 (see Appendix A). In practice, the simulations combined a deterministic and a stochastic component. The deterministic part relied on fixed hourly demand and renewable profiles: for each meteorological year from 1982 to 2024, hourly wind and solar capacity factors were taken from historical records [37] and scaled to 2023 installed capacities, while demand was fixed at the 2023 baseline profile. These inputs were identical across all simulation years. In the adequacy runs, the availability of dispatchable units was modeled stochastically using Monte Carlo simulation. For each generating unit with a given installed capacity and annual availability factor, its operating state in every hour was drawn from an independent Bernoulli distribution, as shown in Equation (4):

$$X_{j,t} \sim \text{Bernoulli}(AFA_j) \quad (4)$$

The total available dispatchable generation capacity in a given hour was then obtained as the sum of the products of unit capacities and their respective binary availability states (Equation (5)):

$$\text{TOT_CAP}_t^{\text{disp}} = \sum_j \text{CAP}_j \times X_{j,t} \quad (5)$$

where

$X_{j,t}$ —binary availability state of unit j in hour t (1 = available, 0 = unavailable);

AFA_j —annual availability factor of unit j ;

CAP_j —installed capacity of unit j [MW];

$\text{TOT_CAP}_t^{\text{disp}}$ —total available dispatchable generation capacity in hour t [MW].

For each meteorological year, 100 Monte Carlo simulations were performed, and the resulting hourly adequacy states were used to compute ELCC and EFC values.

In the ELCC method, the initial reliability of the system was established by calculating LOLE for a reference system without weather-dependent generation (e.g., LOLE = 8 h). Next, the hourly wind or solar generation profile (depending on the technology considered) was added to the system, which reduced residual demand and lowered LOLE (e.g., to 4 h). To quantify the ELCC, system demand was then uniformly increased across all hours until the LOLE returned to its original reference level (e.g., LOLE = 8 h). The additional load that could be reliably supported as a result of the renewable integration defines the Effective

Load Carrying Capability (ELCC). This value, expressed in megawatts, was subsequently used to calculate the capacity credit according to Equation (6):

$$CC = \frac{ELCC}{Capacity} \times 100 \quad (6)$$

where

CC—capacity credit [%];

ELCC—Effective Load Carrying Capability, defined as the additional system load that can be reliably served due to the integration of wind or solar generation while maintaining the original system reliability level (e.g., unchanged LOLE) [MW];

Capacity—installed capacity of the analyzed renewable technology (e.g., wind or solar); [M.W.]

×100—operation used to express the result as a percentage.

The EFC method followed a similar structure but employed a different logic to isolate the contribution of a specific renewable source. First, the synthetic hourly series of available dispatchable generation capacity was combined with hourly wind and solar generation profiles. System demand was then increased until a predefined LOLE target was reached (e.g., LOLE = 4 h), establishing the reference reliability level. Subsequently, either the wind or solar profile was removed—depending on the technology under consideration—while the other was retained. This removal caused LOLE to increase (e.g., to 8 h) due to the loss of the respective renewable generation. To restore LOLE to the original target (4 h), a perfectly reliable firm capacity was added to the system. The amount of added firm capacity, expressed in megawatts, defines the Equivalent Firm Capacity (EFC) of the removed renewable source. The corresponding capacity credit was then calculated as the ratio of the EFC to the installed capacity of the respective renewable technology, as shown in Equation (7):

$$CC = \frac{EFC}{Capacity} \times 100 \quad (7)$$

where

CC—capacity credit [%];

EFC—Equivalent Firm Capacity, defined as the amount of perfectly reliable firm capacity required to replace the removed VRES while maintaining the original system reliability level (e.g., unchanged LOLE) [MW];

Capacity—installed capacity of the analyzed renewable technology (e.g., wind or solar) [MW];

×100—operation used to express the result as a percentage.

To summarize, three complementary methods were applied to estimate the capacity credit of wind and solar power plants. All rely on hourly demand and generation time series but differ in how they represent reliability and system response. The LDC method highlights how renewables reshape the timing and magnitude of net peak load, whereas ELCC and EFC quantify their adequacy contribution through probabilistic metrics. Figure 2 schematically outlines the computational steps for each method.

In terms of scope and complexity, the LDC method is transparent and easy to implement but cannot fully capture stochastic demand–generation interactions. ELCC offers a reliability-based benchmark grounded in LOLE analysis, though it requires more detailed data and higher computational effort. EFC complements ELCC by expressing renewable contributions as equivalent firm capacity, which is intuitive for benchmarking but less commonly applied and sensitive to the chosen reliability target. Together, these methods provide complementary perspectives for assessing the adequacy contribution of variable

renewables. Together, these methods provide complementary perspectives for assessing the adequacy contribution of variable renewables and constitute a rigorous framework to quantify their contribution under different reliability standards, ensuring comparability with both Polish and international benchmarks.

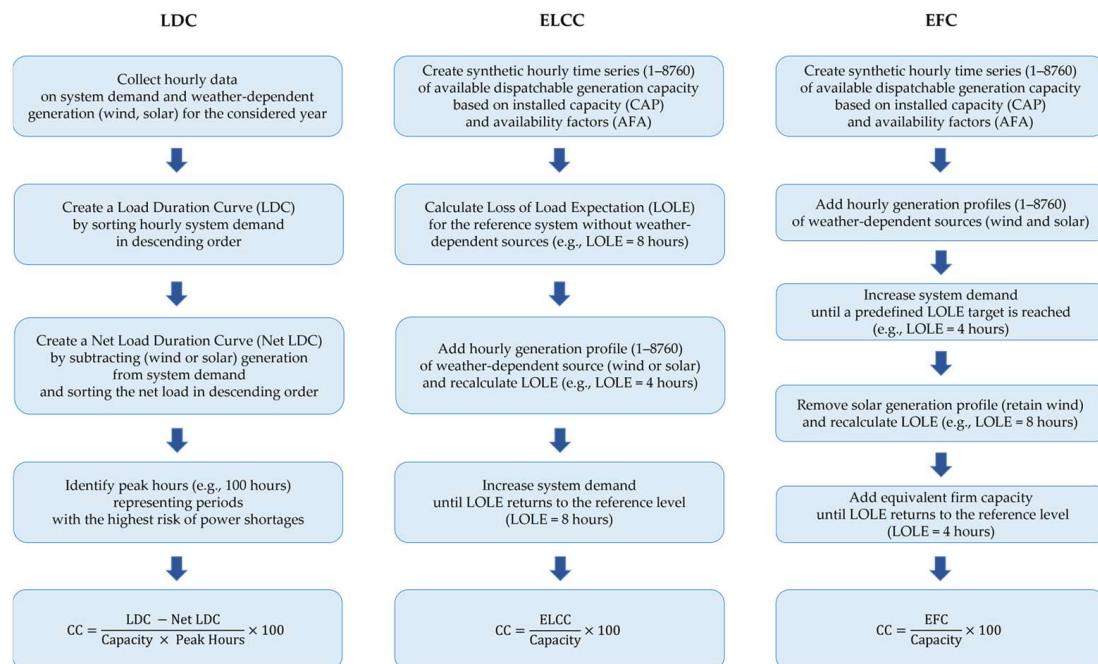


Figure 2. Computational steps in LDC, ELCC and EFC methods for capacity credit estimation.

3. Results

This section presents the numerical results of the capacity credit analysis conducted for wind and solar power plants. The results were derived from simulations based on hourly time series data and reflect the application of distinct three methodological approaches. The following subsections provide a comparative overview of the outcomes obtained using the LDC, ELCC, and EFC methods, with particular attention to differences in estimated capacity credit values depending on the approach applied. The section concludes with a consolidated summary, offering a side-by-side comparison of all methods and technologies considered.

3.1. LDC Method

The capacity credits obtained using the LDC method for wind and solar power plants in 2021–2024 are presented in Table 1. The analysis was performed for the 100 highest hourly demand periods (peak hours) identified in each year. For each renewable source, the capacity credit was calculated according to Equation (1), representing the average contribution of the given technology during these selected hours. To provide additional insight into variability, the table also reports minimum and maximum values derived using Equation (2). These extreme values capture the lowest and highest observed contributions of wind or solar generation during the 100 peak hours, highlighting the potential range of support each technology can provide during critical periods of system operation.

Table 1. Capacity credits for wind and solar power plants derived using the LDC method for the years 2021–2024 in %.

Year		2021		2022		2023		2024	
Technology		Wind	Solar	Wind	Solar	Wind	Solar	Wind	Solar
CC	min	4.43	2.55	6.45	1.81	5.42	1.22	7.76	2.72
	avg	9.58	4.10	9.19	2.36	9.40	2.12	17.27	4.15
	max	14.12	5.04	10.46	3.48	10.51	2.64	22.22	5.07

The LDC-based estimates show significant variation across technologies and years. Wind capacity credits displayed a broad annual range, with average values relatively stable between 9.19% and 9.58% in 2021–2023, followed by a sharp increase to 17.27% in 2024. Minimum and maximum values also reflected this trend, with a wider spread in 2024 (7.76% to 22.22%), suggesting more favorable conditions for wind generation during peak demand periods. In contrast, solar capacity credits remained generally lower, with averages ranging from 2.12% in 2023 to 4.15% in 2024. Year-to-year variability was more pronounced for solar, particularly in minimum values, which dropped to 1.22% in 2023. Maximum solar contributions remained below 5.10% in all years, confirming the limited alignment of solar output with evening demand peaks.

These results highlight the importance of considering both average and extreme values in adequacy assessments. While average capacity credit offers a useful benchmark for system planning, the inclusion of minimum and maximum values underscores the uncertainty and variability inherent to renewable generation during periods of high system stress. The consistent outperformance of wind relative to solar, combined with the wide range between minimum and maximum values—particularly for wind—illustrates the sensitivity of results to the temporal dynamics of demand and generation and to the specific hours considered.

Figures 3–6 graphically illustrate the results for the 100 highest-demand hours in 2021–2024. Each figure shows the sorted LDC (black solid line) alongside the corresponding Net LDCs for wind and solar, depicted as blue and yellow solid lines, respectively. These curves were obtained by subtracting hourly renewable generation from system demand and sorting the residual values in descending order. Additionally, the hourly capacity credit values derived from Equation (2) are displayed as blue (wind) and yellow (solar) bars, enabling a detailed examination of adequacy contributions during each of the 100 critical hours. These visualizations complement the numerical results in Table 1 and further highlight the variability in renewable performance during stressed system conditions.

In addition to the LDC/Net LDC comparisons, the temporal distribution of the 100 peak load hours and the corresponding net peak load hours (after accounting for wind and solar generation) was examined to identify recurring patterns. Figures 7–10 show how these hours are distributed by hour of day and day of week for each year from 2021 to 2024. This analysis provides additional insights into how the timing of system stress shifts depending on the renewable source considered and underscores the temporal mismatch between peak demand and renewable output.

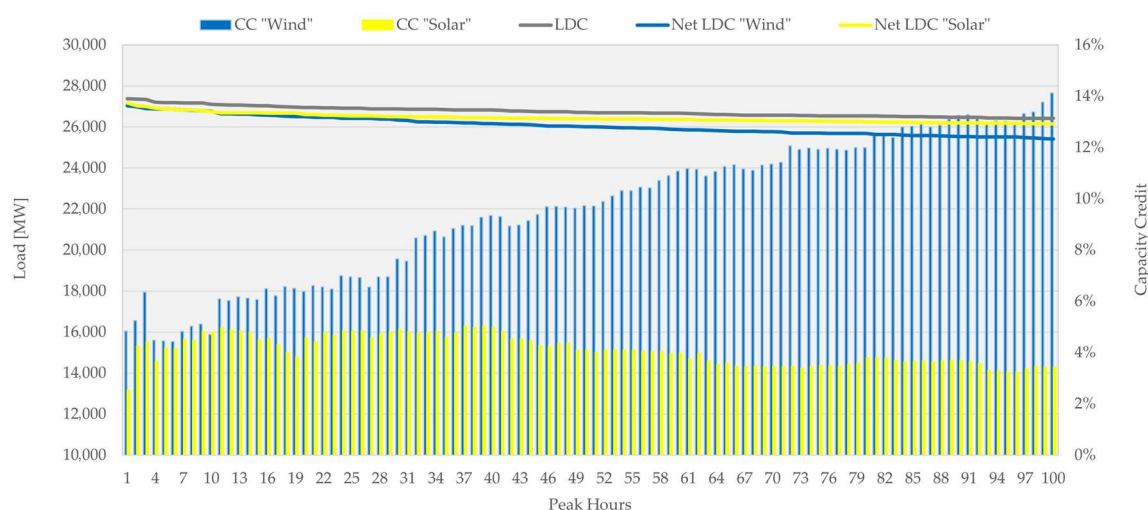


Figure 3. Capacity credit of wind and solar in 2021 based on LDC and Net LDC analysis.

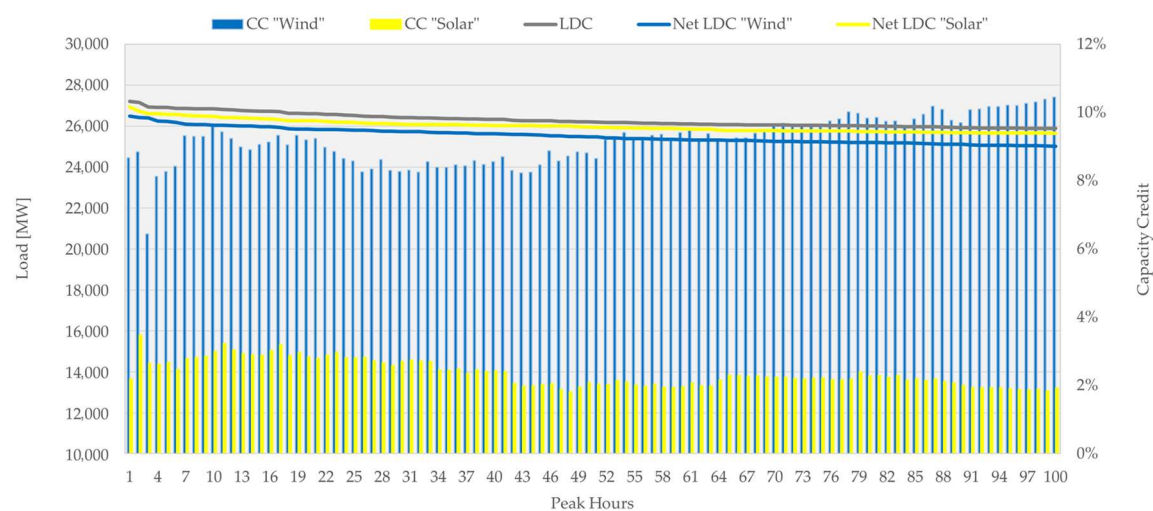


Figure 4. Capacity credit of wind and solar in 2022 based on LDC and Net LDC analysis.

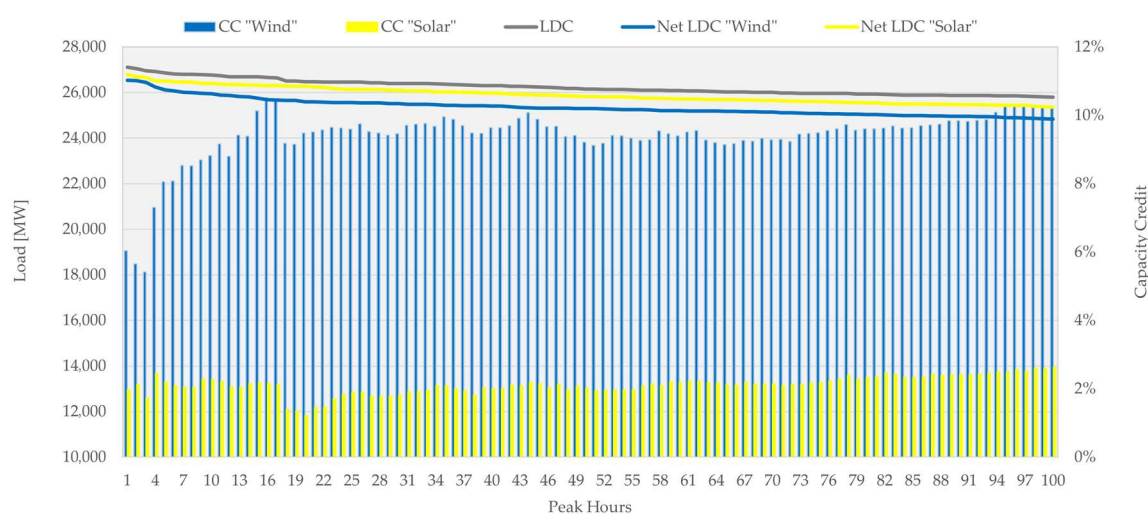


Figure 5. Capacity credit of wind and solar in 2023 based on LDC and Net LDC analysis.

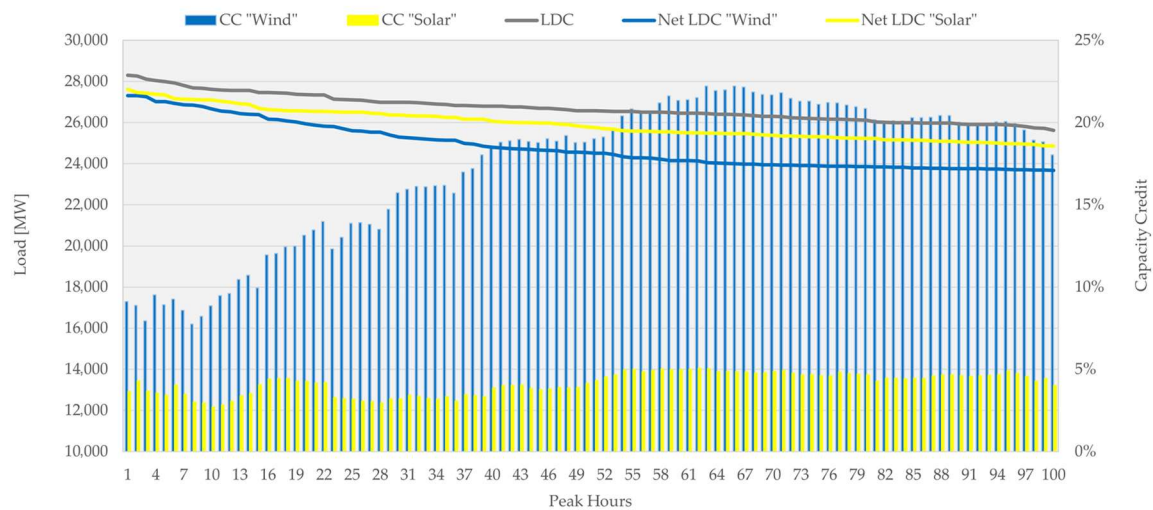


Figure 6. Capacity credit of wind and solar in 2024 based on LDC and Net LDC analysis.

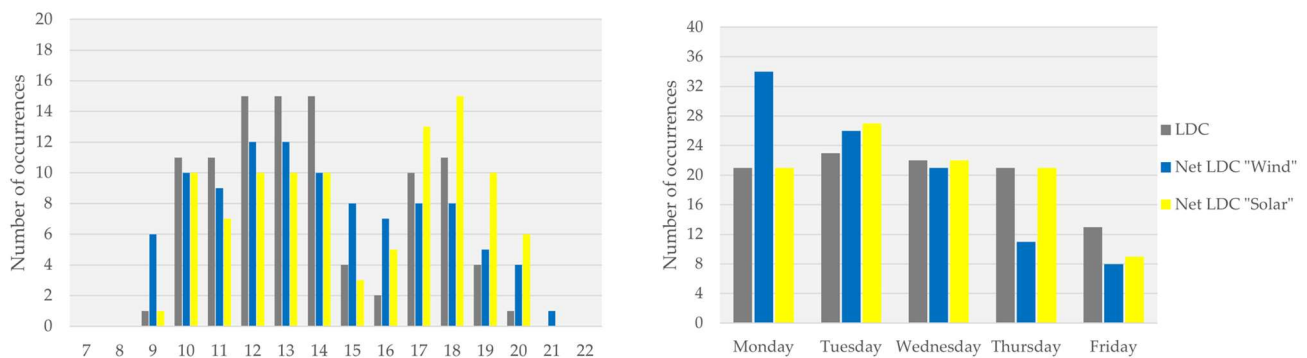


Figure 7. Hourly (left) and weekly (right) distribution of the 100 peak load hours and net peak load hours for wind and solar in 2021.

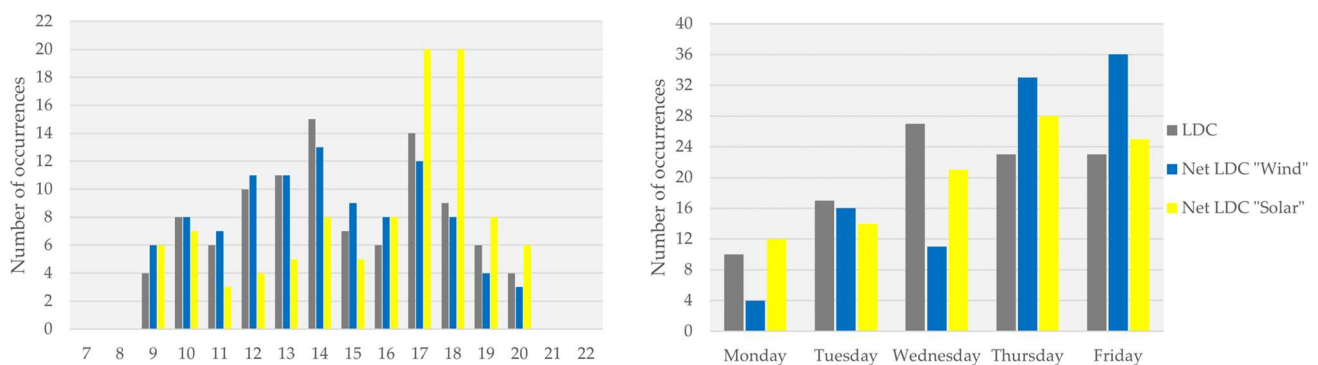


Figure 8. Hourly (left) and weekly (right) distribution of the 100 peak load hours and net peak load hours for wind and solar in 2022.

The results indicate that variable renewable generation significantly reshapes the timing of net peak load hours. For solar, a consistent shift was observed from midday, when solar output is high, toward late afternoon and evening, when solar production declines and residual demand rises. This demonstrates solar's strong impact on reducing daytime peaks but also its limited contribution during evening demand periods. For wind, the effect was less uniform: in some cases, wind generation helped alleviate evening peaks, while in others its contribution was minimal or misaligned with demand. This irregularity reflects the stochastic nature of wind resources.

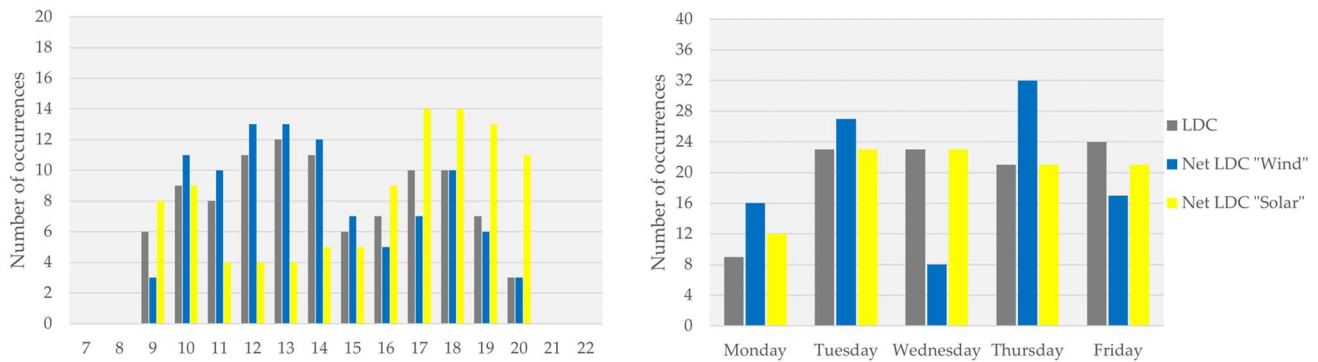


Figure 9. Hourly (left) and weekly (right) distribution of the 100 peak load hours and net peak load hours for wind and solar in 2023.

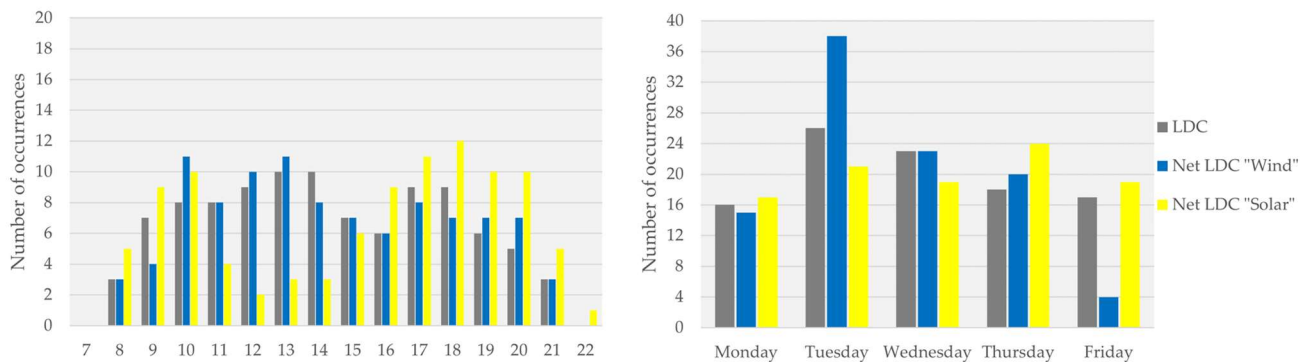


Figure 10. Hourly (left) and weekly (right) distribution of the 100 peak load hours and net peak load hours for wind and solar in 2024.

Across all years, both peak load hours and net peak load hours occurred exclusively on weekdays, with no such events on weekends. This underlines the strong link between peak system stress and typical workday consumption patterns, reinforcing the importance of temporal alignment between renewable generation and demand in adequacy assessments.

3.2. ELCC and EFC Method

The capacity credits for wind and solar power plants calculated using the ELCC and EFC methods for 2021–2024 are summarized in Table 2. The analysis was based on probabilistic reliability metrics applied over the full annual horizon, capturing the temporal correlation between renewable generation and system demand. For each year and technology, capacity credits were calculated using Equation (6) for ELCC and Equation (7) for EFC. The results provide a comprehensive assessment of the adequacy contribution of variable renewable energy sources under different system conditions throughout the year.

Table 2. Capacity credits for wind and solar power plants calculated using the ELCC and EFC methods for the years 2021–2024 in %.

Year		2021		2022		2023		2024	
Technology		Wind	Solar	Wind	Solar	Wind	Solar	Wind	Solar
CC	ELCC	11.37	5.88	10.33	3.09	8.85	2.73	12.61	4.46
	EFC	8.93	6.60	8.08	1.82	8.37	2.45	11.19	4.57

The analysis of ELCC and EFC results for 2021–2024 shows clear interannual variability and differences between the two methods. For wind, ELCC values ranged from 8.85% in

2023 to 12.61% in 2024, consistently exceeding the corresponding EFC values (8.08–11.19%). This indicates that wind generation provided a stable and moderate contribution to system adequacy during the analyzed period. In contrast, solar capacity credits were generally lower and exhibited stronger year-to-year fluctuations. ELCC values declined from 5.88% in 2021 to 2.73% in 2023, before partly recovering to 4.46% in 2024. A similar pattern was observed for EFC, ranging from 6.60% in 2021 to a minimum of 1.82% in 2022. These variations reflect the changing coincidence between solar output and peak system stress, which directly affects its firm capacity contribution under LOLE-based metrics. Overall, wind consistently achieved higher and more stable capacity credits than solar under both methods, confirming its greater reliability in supporting adequacy. The divergence between ELCC and EFC further underlines the sensitivity of capacity credit estimates to the chosen methodological approach.

To explore interannual variability, ELCC and EFC calculations were extended to historical wind and solar generation profiles from 1982 to 2024. A fixed demand profile and dispatchable generation structure corresponding to 2023 were applied to isolate the impact of renewable variability. Figure 11 presents the resulting capacity credit distributions, including the median values (solid line) and the 5th–95th percentiles (shaded area) across the full range of meteorological years.

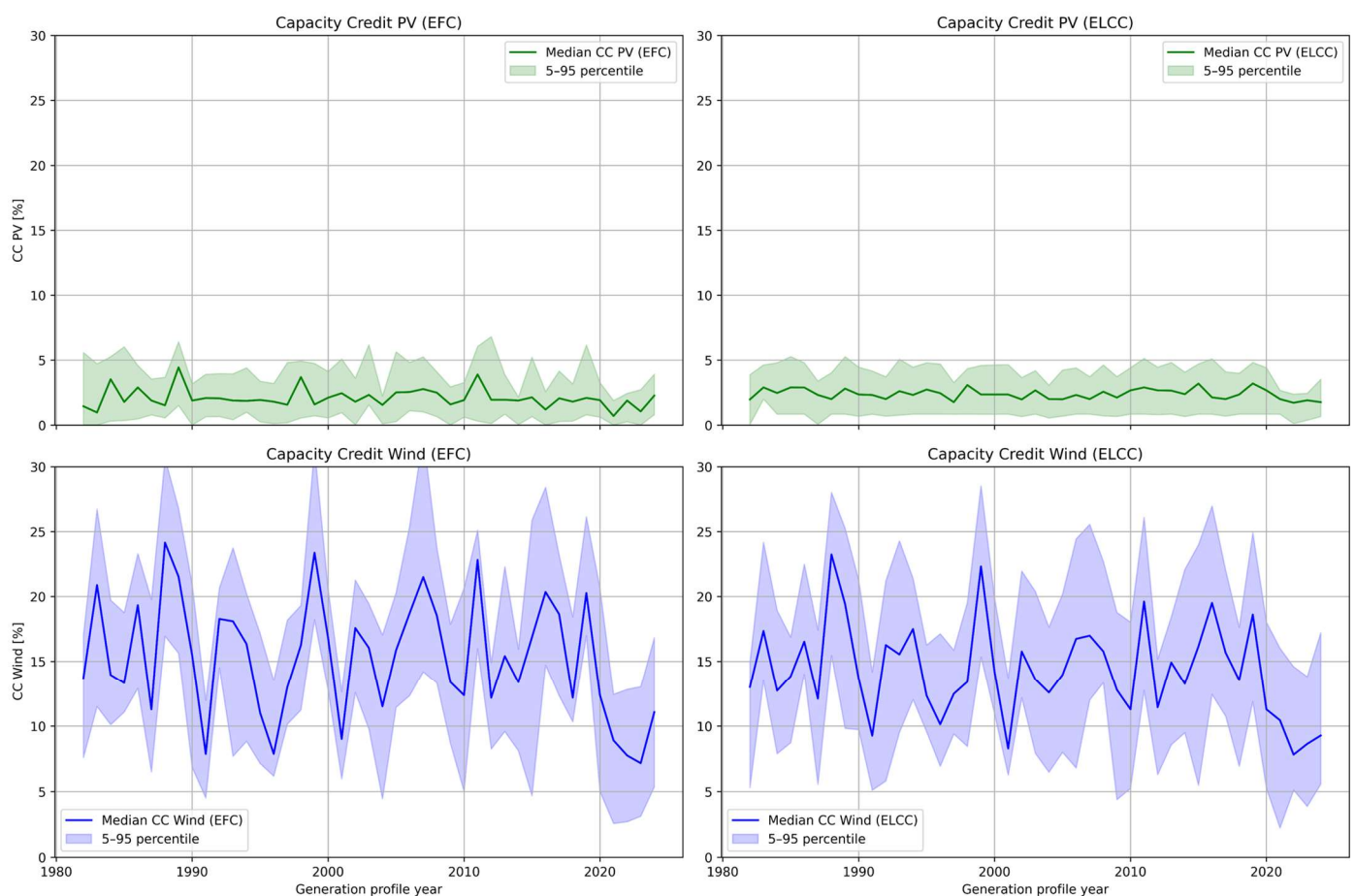


Figure 11. Capacity credit estimates for wind and solar power plants using ELCC and EFC methods under interannual variability of renewable generation (1982–2024), with demand and dispatchable generation structure for 2023.

The results confirm that capacity credit values are highly sensitive to interannual variability in renewable generation. For solar, both ELCC and EFC values remained relatively low and showed limited variation, typically not exceeding 5%. This outcome

reflects the misalignment between solar output and the system's critical demand periods, which usually occur in the evening. As a result, solar contributed only modestly to system adequacy, with firm capacity replacement values particularly low under the EFC method.

By contrast, wind exhibited significantly higher and more variable capacity credit values. Both ELCC and EFC results frequently exceeded 15%, especially in years when wind output coincided with peak demand hours. The wide range between the 5th and 95th percentiles illustrates the strong influence of weather-driven fluctuations on wind's adequacy contribution. ELCC values tended to be higher than EFC, especially when wind generation aligned well with periods of system stress, reducing LOLE more effectively. Conversely, when generation was concentrated outside peak hours, EFC dropped, as only minimal firm capacity was needed to replace RES.

These findings reinforce the 2021–2024 results, confirming that wind generally provides a stronger and more reliable adequacy contribution than solar. They also highlight the importance of long-term analysis covering a wide range of meteorological conditions when evaluating capacity credit for variable renewables.

4. Discussion

The discussion focuses on the interpretation of the capacity credit results obtained for variable renewable energy sources, considering the diverse operating conditions of the Polish power system. By applying multiple analytical perspectives, the study identifies patterns, limitations, and factors influencing the reliability of wind and solar power plants in contributing to system adequacy. The variability of these sources, both seasonal and intraday, is analyzed in the context of their alignment with peak demand periods. Furthermore, the calculated indicators are compared with the values used in the Polish capacity market [38–40] to assess their consistency and relevance for planning and investment decisions. A detailed comparison of capacity credit values for 2021–2024 is presented in Table 3, highlighting contrasts between the applied methods and the standardized values used in national capacity market auctions.

Table 3. Capacity credits for wind and solar power plants in the years 2021–2024 derived from the LDC (deterministic) and ELCC/EFC (probabilistic) methods, alongside officially adopted capacity credits from the Polish capacity market auctions in %.

Technology		Wind				Solar			
Year		2021	2022	2023	2024	2021	2022	2023	2024
CC	LDC	9.58	9.19	9.40	17.27	4.10	2.36	2.12	4.15
	ELCC	11.37	10.33	8.85	12.61	5.88	3.09	2.73	4.46
	EFC	8.93	8.08	8.37	11.19	6.60	1.82	2.45	4.57
	capacity market ¹	10.94	10.94	10.94	12.04	2.07	2.07	2.07	1.74

¹ Capacity market values represent standardized availability coefficients (in Polish KWD), used in main auctions to indicate the expected contribution of wind and solar technologies during peak demand periods [33,34].

The results reveal considerable variation in capacity credit estimates, highlighting the influence of the chosen methodological approach. For wind, ELCC values often exceeded those derived from the EFC and LDC methods, particularly in 2021 and 2022, suggesting a more favorable alignment of wind generation with critical periods in probabilistic assessments. The marked increase in the LDC value in 2024 (17.27%) can be attributed to an exceptionally strong correlation between the wind generation profile and peak demand hours in that year. In contrast, capacity credit values for solar remained consistently lower

and more volatile across all methods, reflecting the technology's limited contribution during evening peak demand periods. Interestingly, EFC estimates for solar were occasionally slightly higher than ELCC, especially in 2021 and 2024, which may stem from the way EFC distributes equivalent firm capacity without requiring identical system reliability outcomes.

When compared with the capacity credit values used in the Polish capacity market, clear differences emerge. For wind, official market values generally fell within the range of estimates obtained using the applied methods and closely matched ELCC outcomes in most years. This alignment suggests that the market assumptions for wind are reasonably robust, at least under average conditions. For solar, however, capacity credit values adopted in the market were consistently lower than most calculated estimates. The gap was particularly wide in 2021 and 2024, when solar generation aligned more closely with peak demand. Even in 2022 and 2023, market values remained below LDC-based estimates, indicating a conservative, though not necessarily underestimated, assessment of solar's adequacy contribution. These findings highlight the need for periodic updates of market parameters to reflect evolving generation profiles and improved methodological understanding, especially as variable renewables gain prominence in the power system.

The results obtained from the LDC, ELCC, and EFC methods further underscore the significance of capturing temporal variability in wind generation when assessing system adequacy. Although the average values derived using the deterministic LDC method for 2021–2023 (9.19–9.58%) are broadly consistent with the standardized availability coefficients used in the capacity market (10.94%), this apparent agreement may conceal substantial interannual and intrayear fluctuations. In particular, minimum values observed in historical data for the same period were far below these averages, pointing to the possibility of much lower contributions during specific high-stress hours. By contrast, probabilistic methods such as ELCC and EFC explicitly capture this variability, accounting not only for median outcomes but also for uncertainty and reliability constraints under diverse system conditions. The spread between ELCC and EFC values, especially for wind, illustrates the sensitivity of adequacy estimates to the temporal alignment of generation with peak demand. These observations highlight both the strengths and the limitations of current modeling practices, and the importance of refining them to better reflect the variability of wind generation and its role in adequacy assessments.

For solar, the results confirm its limited contribution to system adequacy during peak demand periods, regardless of method. Across all approaches, capacity credit values remained low, generally between 2% and 4%, underscoring the weak correlation between solar output and system peak hours. The LDC-derived values for 2022 (2.36%) and 2023 (2.12%) were relatively close to those adopted in the capacity market (2.07%), suggesting that current market assumptions remain broadly realistic. Nevertheless, ELCC and EFC results show that in specific years, even these conservative estimates may prove slightly optimistic. These insights highlight the need for caution when assessing solar's role in adequacy, particularly in contexts where evening peak demand drives reliability needs.

Overall, the comparative findings emphasize the necessity of a more granular and adaptive framework for estimating capacity credits, especially for variable renewables. While standardized availability coefficients streamline market operations, they may not fully reflect the actual contribution of wind and solar power plants under evolving conditions. In broader adequacy assessments, it is also important to account for both short-term aspects such as forecast accuracy and reserve capacity, as well as longer-term factors including meteorological variability, seasonal effects, and extreme events, which together complement capacity credit in capturing the full reliability challenge. This comparison confirms that the adopted research design, integrating deterministic and probabilistic perspectives, is well suited to capture the complex adequacy contributions of VRES under

evolving system conditions. In addition, the analysis provides system-specific coefficients that can serve as calibrated inputs to long-term capacity expansion models such as TIMES, where adequacy constraints depend on effective rather than installed capacity. This strengthens the link between adequacy studies and optimization-based system planning. It should also be noted that storage resources, although present in the Polish system, were not explicitly modeled in this study. Their exclusion represents a limitation, since storage can mitigate net load variability, reduce curtailment, and enhance the effective adequacy contribution of VRES. This aspect has therefore been highlighted as a key direction for future research.

5. Conclusions

This study investigates the contribution of variable renewable energy sources—specifically onshore wind and solar photovoltaics—to system adequacy in Poland amid the ongoing energy transition aligned with the European Union’s 2050 climate neutrality goals. Between 2020 and 2025, the installed capacities of onshore wind and solar photovoltaics in Poland increased significantly, reaching nearly 11 GW and more than 22 GW, respectively. Concurrently, system peak demand exceeded 28 GW in 2024, highlighting the growing complexity of balancing supply and demand in a system with high penetration of weather-dependent sources.

Two methodological approaches were employed to evaluate the adequacy contribution of wind and solar power plants, using capacity credit as a key indicator: a deterministic approach based on the Load Duration Curve (LDC) method, and a probabilistic approach incorporating the Effective Load Carrying Capability (ELCC) and Equivalent Firm Capacity (EFC) methods. The LDC method, relying on historical generation and demand data, proved to be a practical tool for estimating capacity credit in contexts where only empirical data are available. The results obtained with this method were generally consistent with the capacity credit values used in the Polish capacity market. In contrast, the probabilistic methods provided a more comprehensive perspective, as they explicitly captured the co-variation between VRES generation and system demand. The analysis shows that methodological choices directly shape adequacy outcomes, underscoring the need to consider both deterministic and probabilistic perspectives in research and policy contexts.

The results for 2021–2024 indicate that the capacity credit of wind ranged from 8.08% to 17.27%, while that of solar ranged from 1.82% to 6.60%, depending on the method and year. The low solar capacity credit is primarily due to its temporal mismatch with peak demand, which typically occurs during winter evenings when solar generation is minimal. Solar output is highest during midday and exhibits pronounced seasonal variability. Wind generation, in contrast, is driven by meteorological conditions that vary across hourly, daily, and seasonal timescales. This variability calls for additional seasonal adequacy assessments.

Despite the availability of 1.7 GW of pumped storage and 4.4 GW of battery-based storage systems contracted within the capacity market, the relatively low capacity credit values of VRES underline the continued necessity of dispatchable, flexible generation capacity, including gas-fired units, hydropower, and demand response. In systems with high solar penetration, net load curves exhibit a midday drop followed by a steep evening ramp—commonly known as the “duck curve”—posing operational challenges. Olczak et al. [41] indicate that in the Polish context such ramps may reach up to 1.6 GW, further illustrating the scale of variability that must be managed in system operation. In wind-dominated systems, net load can be highly volatile and unpredictable, particularly during nighttime hours, further complicating balancing operations. While renewable generation may also cause curtailment during periods of surplus, the low capacity credit highlights

the inability of VRES to contribute sufficiently during peak demand periods. Curtailment and capacity credit thus represent two sides of the same coin, both signaling the need for firm capacity investments.

The comparison of the deterministic LDC method with the probabilistic ELCC and EFC methods reveals that differences primarily arise from how each method accounts for the temporal correlation between VRES generation and system demand. While LDC provides practical estimates based on historical data, ELCC and EFC offer a more nuanced assessment by capturing variability and alignment with peak demand, highlighting the importance of method selection for planning and operational decisions.

The findings emphasize the importance of embedding capacity credit values in capacity expansion and market design models to support cost-effective and reliable decarbonization pathways. Accurate estimation of VRES contribution to system adequacy is critical not only for operational planning but also for shaping investment signals in renewables, storage technologies, and dispatchable backup capacity.

Current market mechanisms, including the Polish capacity market, do not fully incentivize the development of firm capacity aligned with the evolving needs of a power system dominated by VRES. Future efforts should therefore focus on enhancing adequacy assessment frameworks by incorporating cross-border electricity exchanges and demand response potential. These improvements are essential to ensure the long-term resilience of the Polish power system and to align national adequacy planning with the European Union’s integrated electricity market and climate objectives. In addition, future research should extend to other renewable technologies, particularly offshore wind, and include a more explicit treatment of storage, whose ability to smooth net load ramps and improve adequacy makes it a crucial component of future assessments.

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Appendix A

Table A1. List of dispatchable generating units used in the adequacy simulations, with corresponding fuel types, installed capacities (MW), and annual availability factors (AFA). The data cover units operating in the Polish power system during 2021–2024.

Code	Fuel	Capacity [MW]	AFA [%]	Code	Fuel	Capacity [MW]	AFA [%]
ADA 2-06	Natural gas	600	0.95	LZA 31-10	Hard coal	225	0.90
BEL 2-02	Lignite	370	0.85	LZA 32-11	Hard coal	225	0.90

Table A1. Cont.

Code	Fuel	Capacity [MW]	AFA [%]	Code	Fuel	Capacity [MW]	AFA [%]
BEL 2-03	Lignite	380	0.85	LZA 32-12	Hard coal	225	0.90
BEL 2-04	Lignite	380	0.85	OPL 1-01	Hard coal	386	0.90
BEL 2-05	Lignite	380	0.85	OPL 1-02	Hard coal	383	0.90
BEL 4-06	Lignite	394	0.85	OPL 4-03	Hard coal	383	0.90
BEL 4-07	Lignite	390	0.85	OPL 4-04	Hard coal	380	0.90
BEL 4-08	Lignite	390	0.85	OPL 4-05	Hard coal	905	0.90
BEL 4-09	Lignite	390	0.85	OPL 4-06	Hard coal	905	0.90
BEL 4-10	Lignite	390	0.85	OSB 1-03	Hard coal	230	0.90
BEL 4-11	Lignite	390	0.85	OSB 2-01	Hard coal	230	0.90
BEL 4-12	Lignite	390	0.85	OSB 2-02	Hard coal	230	0.90
BEL 4-14	Lignite	858	0.85	OSC 4-01	Natural gas	782	0.95
DOD 2-05	Hard coal	222	0.90	PAT 11-01	Lignite	222	0.85
DOD 2-06	Hard coal	222	0.90	PAT 12-02	Lignite	222	0.85
DOD 4-07	Hard coal	224	0.90	PAT 12-05	Lignite	200	0.85
DOD 4-08	Hard coal	232	0.90	PAT 2 4-09	Lignite	474	0.85
DOD 4-10	Natural gas	717	0.95	PLO 4-01	Natural gas	630	0.95
DOD 4-09	Natural gas	717	0.95	POL 1-01	Hard coal	225	0.90
GRU 4-01	Natural gas	575	0.95	POL 2-02	Hard coal	242	0.90
JW2 4-07	Hard coal	910	0.90	POL 2-03	Hard coal	242	0.90
JW3 1-03	Hard coal	225	0.90	POL 2-04	Hard coal	242	0.90
JW3 2-01	Hard coal	225	0.90	POL 4-05	Hard coal	242	0.90
JW3 2-02	Hard coal	225	0.90	POL 4-06	Hard coal	242	0.90
JW3 2-04	Hard coal	225	0.90	POL 4-07	Hard coal	239	0.90
JW3 2-05	Hard coal	220	0.90	RYB 1-03	Hard coal	225	0.90
JW3 2-06	Hard coal	225	0.90	RYB 2-04	Hard coal	225	0.90
KAR 1-02	Hard coal	100	0.90	RYB 2-05	Hard coal	225	0.90
KAR 1-03	Hard coal	112	0.90	RYB 2-06	Hard coal	225	0.90
KAR 1-04	Natural gas	122	0.95	RYB 4-07	Hard coal	225	0.90
KOZ 11-02	Hard coal	228	0.90	RYB 4-08	Hard coal	225	0.90
KOZ 11-06	Hard coal	228	0.90	SIA 1-01	Hard coal	153	0.90
KOZ 12-01	Hard coal	228	0.90	SIA 1-02	Hard coal	153	0.90
KOZ 12-03	Hard coal	225	0.90	STW 42-12	Natural gas	450	0.95
KOZ 12-04	Hard coal	228	0.90	TUR 1-01	Lignite	250	0.85
KOZ 12-05	Hard coal	228	0.90	TUR 2-02	Lignite	250	0.85
KOZ 12-07	Hard coal	220	0.90	TUR 2-03	Lignite	250	0.85
KOZ 12-08	Hard coal	228	0.90	TUR 2-04	Lignite	261	0.85
KOZ 24-09	Hard coal	566	0.90	TUR 2-05	Lignite	261	0.85
KOZ 24-10	Hard coal	566	0.90	TUR 2-06	Lignite	261	0.85
KOZ 24-11	Hard coal	1075	0.90	TUR 4-11	Lignite	496	0.85
LGA 4-10	Hard coal	460	0.90	WLC 2-01	Natural gas	465	0.95
LZA 31-09	Hard coal	230	0.90	WZE 22-20	Natural gas	497	0.95

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