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# Empirical Assessment of Wind Power's Capacity Credit: A European Case Study

Dubravko Sabolić, Igor Ivanković

***Summary*** **— This paper presents an empirical analysis of the intrinsic capacity credit of onshore wind power across twelve European countries, based on hourly measured data for 2019 and 2024. Capacity credit was calculated as a function of acceptable default risk, under the simplifying assumption that wind power alone must satisfy total demand, serving as a limiting-case benchmark for adequacy assessment. The results show a wide range of outcomes across individual countries and highlight the effects of spatial aggregation, where the combined regional system performs better than its constituents. A nonlinear model was fitted to describe the relationship between capacity credit and risk probability. Additionally, several hypothetical spatial distributions of installed capacity were evaluated using statistical criteria, illustrating how coordination could affect adequacy outcomes. The analysis was based exclusively on observed data, without additional modeling assumptions, and the proposed method offers a transparent, generalizable framework for empirical adequacy benchmarking across generation types and planning contexts.**

***Keywords*** **— Wind power, capacity credit, system adequacy, spatial distribution, empirical modeling**

## I. Introduction

Integration of renewable energy sources (RES) into modern power systems poses significant challenges related to system adequacy, short-term variability, and market integration. A variety of methodologies have been proposed to quantify the reliability contribution, or capacity credit, of wind and solar power.

*Capacity credit*, also known as capacity value, is defined as the contribution that a new generator makes to system adequacy without compromising overall reliability. In the context of RES investments, it reflects the share of system load that can be reliably met by new RES generation, accounting for its variability and alignment with system stress periods. It is typically expressed as a percentage. For example, if a wind plant has a capacity credit of 10%, only one-tenth of its installed capacity can be counted toward meeting the system's peak load with a high degree of reliability, typically around 99% to 99.9% of the time. This reliability depends on the criteria set by the TSO, often defined by the Loss of Load Expectation (LOLE) or Loss of Load Probability (LOLP) [1], [2].

Ensslin et al. [1] observe that onshore wind capacity credits in various systems ranged from as high as 40% of installed capacity in regions with low wind penetration and high capacity factors during peak load times to as low as 5% in regions with high wind penetration or low capacity factors. Jorgenson et al. [3] conducted a comprehensive evaluation of wind capacity credit across the Western United States using probabilistic reliability methods. Their findings show that the capacity credit of land-based wind varies significantly by region and weather year, ranging from 5% to 30%, and averages 16%. The study also demonstrates that capacity credit tends to increase with the capacity factor, but that correlation with times of system stress is an even more decisive factor—particularly for offshore wind, which shows substantially higher capacity credit due to better alignment with periods of high demand and system risk. Ssengonzi et al. [4] present an approach to estimating the capacity credit of RES, particularly wind and solar, as their penetration levels increase across regional power grids in the contiguous United States, concluding that the capacity credits for all RES technologies analyzed decrease with penetration rate, with 5% as a limiting order of magnitude at the regional level.

Relying solely on wind power without supporting technologies would require a significant degree of overbuilding to ensure system adequacy, due to its variability and limited firm capacity. In practice, the need for such excessive overbuilding can be significantly reduced even in a hypothetical fossil-free system through the integration of complementary assets such as flexible hydropower, energy storage systems, demand-side management, and potentially hydrogen-fired generation. These technologies can mitigate the effects of intermittency and improve the firm capacity contribution of wind, thus lowering the effective overbuild factor required to meet reliability targets.

The statistical properties of generation intermittency in a large wind power system in the USA, along with the resulting demand for regulation reserves, were thoroughly analyzed in [5] and later extended in [6] using a European dataset. Interestingly, both analyses identified the same statistical distribution governing short-term production variations, despite being based on data from fundamentally different systems and geographical contexts.

These statistical findings illustrate how physical characteristics of wind generation affect system-level reliability metrics, forming the foundation for capacity credit analysis.

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## II. The Data

The source of all data used in this study is the ENTSO-E Transparency Platform (https://transparency.entsoe.eu/). For this preliminary analysis, we selected hourly measured aggregate generation data from onshore wind power plants in twelve European countries, as well as the total hourly electricity consumption recorded in those same countries.

Table I lists the countries included in the study along with basic descriptive statistics for the wind power production time series utilized. Regarding the temporal dimension, two separate calendar years were selected for analysis: 2019. and 2024.

The intermediate years were intentionally omitted due to significant societal and market disruptions during that period. Specifically, 2020 and 2021 were marked by the COVID-19 pandemic and its well-known economic effects on electricity demand and industrial output. In its final quarter, 2021 also saw the onset of severe electricity price disruptions that ended over a decade of relative stability [7]. The situation further escalated in early 2022 with the onset of the war in Ukraine, leading to increased crisis levels and price volatility across energy markets. A gradual stabilization in both the energy sector and the broader economy followed throughout 2023. Including these atypical years would have confounded the baseline analysis aimed at comparability across relatively stable conditions. While we acknowledge the importance of learning from periods of disruption, our objective here is to provide a reference scenario based on operational norms. A broader temporal scope will be considered in future research.

As such, the years chosen for this study represent a relevant and balanced framing: 2019 as the last "normal" year before major disruptions, and 2024 as the first year of renewed market stability under the new circumstances.

In addition to basic descriptive statistics, we computed the pairwise coefficients of determination ($R^2$) between all wind power production vectors to assess the degree of linear correlation among the observed countries. These values reflect how well the variation in one country's wind output can be linearly explained by another. The resulting matrix of $R^2$ values is shown in Table II. The upper triangle of the matrix contains $R^2$ values for the year 2019 (in green), and the lower triangle corresponds to 2024, making the table asymmetric. The color intensity increases with the magnitude of $R^2$. It can be observed that moderately strong correlations in wind power production exist only in a few country pairs (indicated by more intense coloration and higher $R^2$ values), and that these correlations are consistently present in both analyzed years.

The following country codes are used throughout the analysis: AT – Austria, BG – Bulgaria, CRO – Croatia, CZ – Czech Republic, F – France, D+L – Germany and Luxembourg, GR – Greece, PL – Poland, PT – Portugal, RO – Romania, ES – Spain, and SUM – the aggregated total across all listed countries.

As of January 2024, the population (in millions) of these countries was: AT – 9.16, BG – 6.45, CRO – 3.86, CZ – 10.9, F – 48.6, D+L – 84.2, GR – 10.6, PL – 36.6, PT – 10.6, RO – 19.1, ES – 48.6; with a combined total of 278 million [8].

TABLE I
Descriptive statistics of the time series used in this study.

| | | $P$ (GW) | $S$ (%) | $E$ (TWh) | $E/P$ (TWh/GW) | $CF$ (%) | Std. (GW) | Std./$P$ (%) |
|---|---|---|---|---|---|---|---|---|
| 2019 | Austria | 3.035 | 3.36 | 7.97 | 2.63 | 29.98 | 0.82 | 27.11 |
| | Bulgaria | 0.7 | 0.53 | 1.25 | 1.79 | 20.41 | 0.13 | 18.19 |
| | Croatia | 0.616 | 0.62 | 1.46 | 2.37 | 27.07 | 0.14 | 23.31 |
| | Czech Republic | 0.316 | 0.29 | 0.69 | 2.17 | 24.75 | 0.06 | 19.25 |
| | France | 13.61 | 13.80 | 32.70 | 2.40 | 27.43 | 2.66 | 19.53 |
| | Germany+Lux. | 52.946 | 42.26 | 100.17 | 1.89 | 21.60 | 8.77 | 16.57 |
| | Greece | 2.355 | 2.44 | 5.79 | 2.46 | 28.07 | 0.46 | 19.45 |
| | Poland | 5.808 | 6.14 | 14.57 | 2.51 | 28.63 | 1.23 | 21.14 |
| | Portugal | 5.127 | 5.66 | 13.42 | 2.62 | 29.89 | 1.13 | 22.01 |
| | Romania | 2.968 | 2.82 | 6.68 | 2.25 | 25.69 | 0.64 | 21.56 |
| | Spain | 22.961 | 22.08 | 52.35 | 2.28 | 26.03 | 3.47 | 15.13 |
| | SUM | 110.44 | 100 | 237.05 | 2.15 | 24.50 | 13.07 | 11.83 |
| 2024 | Austria | 4.021 | 3.33 | 9.36 | 2.33 | 26.52 | 0.95 | 23.52 |
| | Bulgaria | 0.705 | 0.48 | 1.35 | 1.91 | 21.81 | 0.14 | 19.78 |
| | Croatia | 1.209 | 0.93 | 2.62 | 2.16 | 24.64 | 0.27 | 22.02 |
| | Czech Republic | 0.342 | 0.25 | 0.69 | 2.03 | 23.17 | 0.06 | 17.66 |
| | France | 22.134 | 14.84 | 41.79 | 1.89 | 21.56 | 3.63 | 16.42 |
| | Germany+Lux. | 60.049 | 39.67 | 111.69 | 1.86 | 21.28 | 10.04 | 16.72 |
| | Greece | 5.065 | 3.88 | 10.94 | 2.16 | 24.62 | 0.82 | 16.21 |
| | Poland | 9.583 | 8.45 | 23.78 | 2.48 | 28.42 | 2.13 | 22.25 |
| | Portugal | 5.333 | 4.99 | 14.04 | 2.63 | 29.99 | 1.16 | 21.72 |
| | Romania | 2.958 | 2.25 | 6.33 | 2.14 | 24.38 | 0.65 | 21.82 |
| | Spain | 30.159 | 20.94 | 58.94 | 1.95 | 22.26 | 3.87 | 12.84 |
| | SUM | 141.56 | 100 | 281.52 | 1.99 | 22.71 | 16.54 | 11.68 |

**Legend**: $P$ = Installed capacity. $S$ = Share of installed capacity relative to the total for all displayed countries. $E$ = Energy produced. $CF$ = Capacity factor. Std. = Standard deviation.

TABLE II
Matrix of determination coefficients $R^2$: 2019 (upper triangle, green) and 2024 (lower triangle, red).

| | AT | BG | CRO | CZ | F | D+L | GR | PL | PT | RO | ES |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | 1 | 0.010 | 0.046 | 0.346 | 0.024 | 0.060 | 0.001 | 0.102 | 0.008 | 0.037 | 0.020 |
| BG | 0.035 | 1 | 0.068 | 0.010 | 0.013 | 0.006 | 0.123 | 0.010 | 0.005 | 0.332 | 0.007 |
| CRO | 0.046 | 0.059 | 1 | 0.008 | 0.001 | 0.000 | 0.021 | 0.009 | 0.011 | 0.066 | 0.027 |
| CZ | 0.316 | 0.025 | 0.003 | 1 | 0.138 | 0.509 | 0.010 | 0.466 | 0.002 | 0.024 | 0.012 |
| F | 0.041 | 0.021 | 0.025 | 0.182 | 1 | 0.319 | 0.008 | 0.080 | 0.043 | 0.006 | 0.102 |
| D+L | 0.093 | 0.018 | 0.000 | 0.519 | 0.329 | 1 | 0.007 | 0.427 | 0.000 | 0.005 | 0.010 |
| GR | 0.010 | 0.140 | 0.017 | 0.002 | 0.001 | 0.000 | 1 | 0.001 | 0.000 | 0.020 | 0.000 |
| PL | 0.161 | 0.010 | 0.000 | 0.485 | 0.081 | 0.459 | 0.002 | 1 | 0.000 | 0.016 | 0.002 |
| PT | 0.023 | 0.002 | 0.021 | 0.026 | 0.099 | 0.022 | 0.000 | 0.011 | 1 | 0.006 | 0.545 |
| RO | 0.056 | 0.520 | 0.042 | 0.046 | 0.038 | 0.036 | 0.059 | 0.025 | 0.006 | 1 | 0.011 |
| ES | 0.038 | 0.012 | 0.073 | 0.036 | 0.196 | 0.034 | 0.001 | 0.013 | 0.434 | 0.025 | 1 |

## III. Methodology

The primary objective of this study is to determine the effective capacity credit of onshore wind power plants in selected European countries over the analyzed years. To this end, hourly wind generation data were normalized with respect to the total installed capacity recorded at the end of each respective year. Similarly, the aggregate hourly wind generation for the entire group of twelve countries was normalized by the sum of installed capacities in all of them. While this simplification introduces some error — since installed capacity evolves over the year — the relative yearly growth is relatively small, and thus the approximation remains reasonable. The assumption of exclusive wind supply is not intended to reflect practical system planning but rather to define an upper-bound reference case that enables empirical comparison of adequacy outcomes across different spatial and temporal configurations. System load profiles, expressed as hourly electricity consumption, were normalized by the annual peak hourly demand. The intrinsic capacity credit — here referring strictly to onshore wind — was calculated using the following procedure: the time series of normalized wind generation was multiplied by a scalar factor $F$, and then the normalized system demand series was subtracted from the result. The percentage of hours $r$ in which the resulting series was


Dubravko Sabolić, Igor Ivanković, Empirical Assessment of Wind Power's Capacity Credit: A European Case Study, Journal of Energy, vol. 74 Number 1 (2025), 3–8
https://doi.org/10.37798/2025741711

negative was then determined. The capacity credit $C$, corresponding to a default risk of $r$, is defined as:

$$C = \frac{100}{F} \tag{1}$$

The empirically observed capacity credit values — interpretable as quantiles of a stochastic distribution at a given level of risk — were analyzed as a function of the default risk $r$. It was found that the relationship between $C$ and $r$ exhibits a high degree of correlation with the inverse distribution function of short-term production fluctuations, as previously established in our earlier works [5], [6].

Specifically, we find that the capacity credit can be very accurately modeled as a composite function of the form:

$$C(r) = a \cdot r^{b} + c \cdot r + \varepsilon \tag{2}$$

where $a$, $b$, and $c$ are empirically fitted parameters, and $\varepsilon$ is the residual error term capturing the difference between the observed and modeled values of capacity credit. Both $C(r)$ and $r$ are expressed as percentages. Despite its nonlinearity, the model remains interpretable and tractable for practical use. In addition to directly analyzing the observed capacity credit in individual countries and across the entire contiguous geographic region — spanning the full width of the European continent — this study also investigates hypothetical scenarios in which the spatial distribution of installed wind capacity differs from the actual configuration. These scenarios preserve the measured temporal characteristics of normalized production and consumption while varying the relative distribution of installed capacity.

Several alternative spatial configurations were developed, each optimized to improve general indicators of variability—such as minimizing the overall variance of wind generation or maximizing the ratio of total production to its variability. These simulations illustrate the potential benefits of a more coordinated approach to the geographic allocation of wind capacity. The findings indicate that such hypothetical redistribution strategies could yield a higher intrinsic capacity credit compared to the currently observed configuration. However, as the analysis is based on time series from only two individual years, the conclusions remain indicative rather than definitive, highlighting the need for broader temporal coverage in future research.

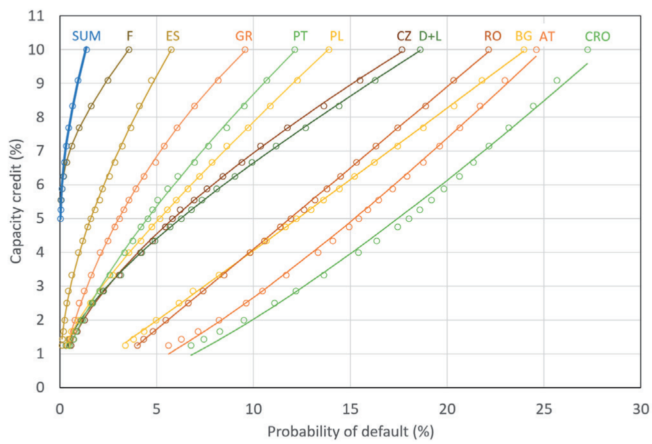


Fig. 1. Capacity credit vs. default probability for 2019.

It is important to emphasize that the intrinsic capacity credit analyzed above was derived through direct empirical observation — essentially "watching nature" — based on measured onshore wind production and total electricity consumption. As such, it inherently captures the full spectrum of stochastic events that occurred during the two years studied, including unpredictable production and demand fluctuations, forced outages, plant shutdowns, localized demand drops, and similar disturbances, which makes it highly relevant within the temporal and geographical scope of the analysis.

Evidently, this type of analysis can be easily extended to include any combination of generation technologies, in any real or simulated configuration, provided that comparable temporal and operational data are available.

## IV. The Results

### A. Actual Spatial Distribution Across the Countries

Figure 1 shows the relationship between capacity credit and the probability of failing to meet instantaneous demand for the year 2019. The dots represent empirically determined values, while the lines correspond to the best-fit regression curves based on (2), obtained by minimizing the total squared error. Figure 2 presents the same type of analysis for the year 2024. Table III summarizes the

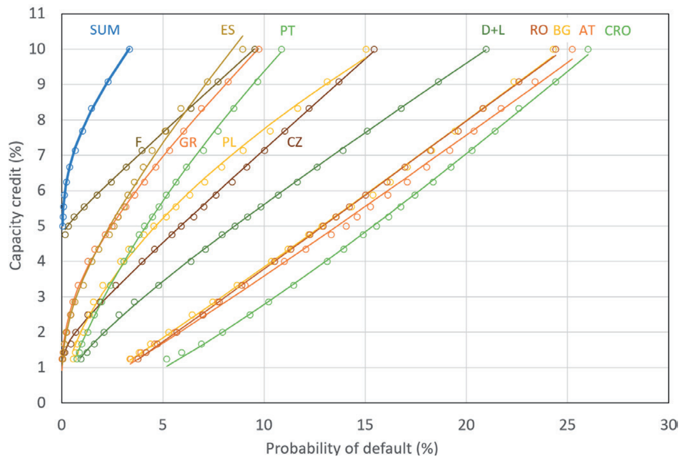


Fig. 2. Capacity credit vs. default probability for 2024.

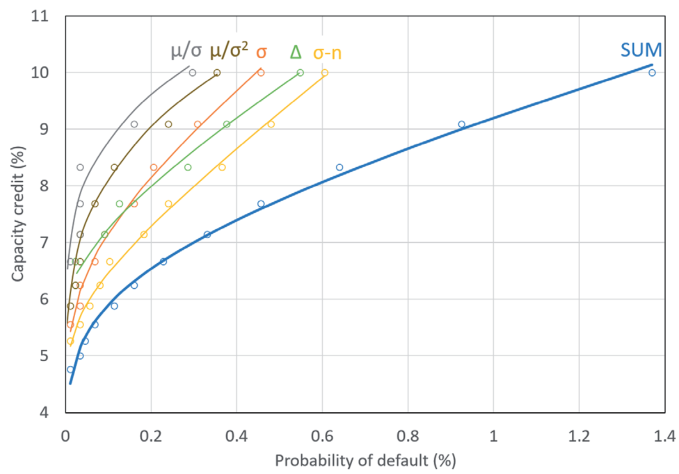


Fig. 3. Capacity credit vs. default probability under multiple hypothetical optimized spatial distributions for 2019.


Dubravko Sabolić, Igor Ivanković, Empirical Assessment of Wind Power's Capacity Credit: A European Case Study, Journal of Energy, vol. 74 Number 1 (2025), 3–8
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Table III

Fitted Regression Parameters and $R^2$ Coefficients for Each Country and Year.

| | | $a$ | $b$ | $c$ | $R^2$ |
|---|---|---|---|---|---|
| 2019 | Austria | -2.935 | 1.062 | 2.830 | 0.9979 |
| | Bulgaria | -2.560 | 1.005 | 2.938 | 0.9996 |
| | Croatia | -2.878 | 1.066 | 2.698 | 0.9936 |
| | Czech Republic | 1.650 | 1.868 | 0.128 | 0.9995 |
| | France | 7.065 | 12.128 | 0.606 | 0.9996 |
| | Germany+Lux. | 1.677 | 2.611 | 0.260 | 0.9997 |
| | Greece | 4.013 | 1.213 | -1.657 | 0.9991 |
| | Poland | 1.556 | 3.150 | 0.463 | 0.9998 |
| | Portugal | 1.608 | 1.642 | 0.215 | 0.9991 |
| | Romania | -0.595 | 8.852 | 0.487 | 0.9998 |
| | Spain | 3.502 | 2.347 | 0.455 | 0.9976 |
| | SUM | 7.808 | 7.359 | 1.403 | 0.9985 |
| 2024 | Austria | -1.720 | 1.018 | 2.010 | 0.9976 |
| | Bulgaria | -0.905 | 1.027 | 1.235 | 0.9989 |
| | Croatia | -1.150 | 1.154 | 1.124 | 0.9991 |
| | Czech Republic | 1.730 | 8.824 | 0.491 | 0.9995 |
| | France | 4.960 | 61.013 | 0.510 | 0.9992 |
| | Germany+Lux. | 0.991 | 2.826 | 0.337 | 0.9997 |
| | Greece | 3.060 | 3.724 | 0.451 | 0.9981 |
| | Poland | 2.094 | 1.717 | -0.026 | 0.9964 |
| | Portugal | 2.738 | 1.166 | -1.035 | 0.9994 |
| | Romania | -0.271 | 3.696 | 0.429 | 0.9995 |
| | Spain | 2.862 | 3.401 | 0.551 | 0.9955 |
| | SUM | 7.134 | 9.552 | 0.573 | 0.9989 |

**Legend**: Regression: $C(r) = a\, r^b + c\, r + \varepsilon$. The probability of default ($r$) and the capacity credit ($C$) are expressed as percentages (%). $R^2$ is the determination coefficient.

fitted regression coefficients and their corresponding $R^2$ values for each case. Residual errors between modeled and observed capacity credit values were generally small — typically below 1.5 percentage points — confirming a close fit between the nonlinear model and the empirical data.

In both analyzed years, two distinct groups of countries can be observed: RO, BG, AT, and CRO on one side, and the remaining countries on the other. The four mentioned countries, at least within the years considered, exhibit insufficient intrinsic capacity credit from wind generation — meaning that reasonable values of capacity credit, on the order of 5 to 10 percent, only occur under relatively unfavorable default risk thresholds. In other words, relying on wind generation as the only renewable generation technology in them would be very costly in terms of additional resources, such as storage facilities, network upgrades, etc., needed to ensure system adequacy and stabilize the grid.

It is also worth noting that in both years, the SUM curve exhibited the most favorable trade-off between probability of default and capacity credit. Specifically, a 10% capacity credit level was attainable with a default probability of just 2–3%, which, while higher than typical reliability targets used by system operators, provides a useful reference point for comparing adequacy outcomes across configurations.

Given the limited scope of this study, these preliminary findings should be revisited and verified using a considerably broader dataset.

## B. Hypothetical Geographic Allocations Yielding Greater Capacity Credit

This naturally raises the question of whether, through hypothetical policies involving quotas for the installation of wind power (or other types of renewable energy), it would be possible — now or in the future—to achieve a higher overall level of system adequacy, that is, a higher capacity credit for the same level of supply risk.

To investigate this, we used the normalized time series of wind generation from all participating countries and determined the optimal relative distribution of installed capacity based on several criteria. These included: minimizing the standard deviation of total production (denoted $\sigma$); minimizing the standard deviation of net production — defined as total generation minus load — (denoted $\sigma$-n); minimizing the maximum absolute hourly change in total production (denoted $\Delta$); maximizing the ratio between total annual energy production and the standard deviation (denoted $\mu/\sigma$); and maximizing the ratio between total annual energy production and the variance (denoted $\mu/\sigma^2$). These symbols are used to distinguish the respective scenarios in Figures 3 and 4.

In all scenarios, the optimized spatial distributions yielded better outcomes than the actual installed capacity distribution. This suggests that, at least in principle and under current electricity consumption profiles, the implementation of coordinated allocation policies could lead to a meaningful improvement in the overall intrinsic capacity credit of this generation technology.

On the other hand, we must emphasize that coordinating such policies at a multinational level across this scale would likely prove extremely challenging, if not infeasible.

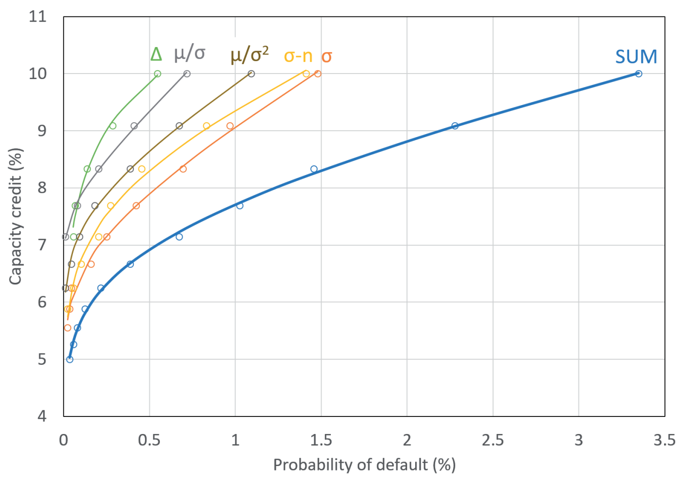


Fig. 4. Capacity credit vs. default probability under multiple hypothetical optimized spatial distributions for 2024.


Dubravko Sabolić, Igor Ivanković, Empirical Assessment of Wind Power's Capacity Credit: A European Case Study, Journal of Energy, vol. 74 Number 1 (2025), 3–8
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Table IV

Optimal Hypothetical Vs. Observed Spatial Distributions of Installed Capacity Across Countries, Based on Selected Optimization Criteria.

| | 2019 | | | 2024 | | |
|---|---|---|---|---|---|---|
| Scenario | Actual | Δ | μ/σ | Actual | Δ | μ/σ |
| Austria | 3.363 | 5.195 | 4.364 | 3.326 | 1.146 | 1.903 |
| Bulgaria | 0.528 | 8.575 | 0 | 0.479 | 9.807 | 0 |
| Croatia | 0.616 | 17.80 | 6.635 | 0.929 | 12.10 | 8.140 |
| Czech Republic | 0.289 | 3.121 | 0 | 0.246 | 2.668 | 1.628 |
| France | 13.80 | 13.89 | 10.40 | 14.84 | 7.185 | 2.196 |
| Germany+Lux. | 42.26 | 0.695 | 7.864 | 39.67 | 8.302 | 8.196 |
| Greece | 2.442 | 8.359 | 24.33 | 3.885 | 3.814 | 28.99 |
| Poland | 6.145 | 8.653 | 11.20 | 8.446 | 6.949 | 9.874 |
| Portugal | 5.663 | 15.65 | 6.239 | 4.987 | 14.38 | 8.026 |
| Romania | 2.818 | 1.810 | 7.833 | 2.248 | 5.291 | 4.316 |
| Spain | 22.08 | 16.25 | 21.14 | 20.94 | 28.35 | 26.74 |

**Legend:** Δ – optimized by the first-order difference; μ/σ – optimized by the ratio of the mean to the standard deviation. All values are expressed as percentages (%).

Figures 3 and 4 illustrate the relationship between capacity credit and default probability under the optimized spatial distributions for 2019 and 2024, respectively. Each curve represents one of the optimization scenarios introduced earlier. In all cases, the curves lie to the left of the reference curve for the actual spatial distribution (SUM), confirming that improved adequacy outcomes can, in principle, be achieved through optimized geographic allocation.

Table IV provides a comparative overview of the optimal relative distribution of installed capacity by country for both analyzed years, along with a comparison to the observed (actual) distribution. For the sake of brevity, the table includes only the results of optimizations according to two specific criteria: the minimum peak absolute hourly change in total production (denoted by the symbol Δ) and the ratio of total annual production to its standard deviation (denoted as $\mu/\sigma$). These results should be interpreted in the context of each country's relative size. Population, as referenced in Section II, serves as a reasonable proxy for national scale, though additional factors—such as the land area available for specific types of power generation—may also be relevant.

For example, in the case of Croatia — which, apart from Luxembourg, is the smallest of the countries included — it would be practically impossible to allocate 17.80% of the total wind capacity, as suggested by the optimization result under the Δ scenario in Table IV for the year 2019. Since the total installed capacity across all countries now exceeds 140 GW, such a share would imply more than 25 GW of wind power within Croatia alone, which is unrealistic given the country's limited territorial area.

Consequently, more advanced future research should incorporate upper bounds on installable capacity per country into the optimization problem, taking into account territorial, regulatory, and political constraints. Other system-level limitations, such as the impact of high wind penetration on reduced system inertia and frequency stability, may also play a role and merit further consideration in future studies.

## V. Discussion And Future Work

The analysis presented in this paper provides a preliminary empirical view of the intrinsic capacity credit of wind power across twelve European countries, highlighting several aspects that may warrant further investigation.

One limitation of the study is the relatively narrow temporal scope, covering only the years 2019 and 2024. These years were deliberately selected to represent conditions before and after a period of significant systemic disruptions. However, expanding the time horizon could help assess the robustness of the observed patterns and improve generalizability. On the other hand, the geographic scope of the study, which includes a diverse cross-section of southern, central, and southeastern Europe with a combined population of 278 million, may provide a representative basis for regional system-level considerations, although it can be broadened, too.

A perhaps noteworthy observation is the similarity in functional form between the dependence of capacity credit on default probability and that of the so-called regulation multiplier—a proxy for the demand for secondary regulation reserves—on default probability, as identified in our earlier studies [5], [6]. Although the variables involved are not the same, and the underlying mechanisms differ, the resemblance in empirical structure invites further examination. At present, the reason for this alignment remains unclear.

Another aspect observed in both analyzed years is that the aggregated capacity credit across all countries consistently exceeded the values obtained for any individual country. This is broadly consistent with the idea that geographic diversification helps mitigate the variability of renewable generation and supports system adequacy.

Results from the hypothetical spatial allocation scenarios suggest that an alternative geographic distribution of installed capacity could lead to improved adequacy outcomes. Although the methodology shows what could, in principle, be achieved, it is unlikely that such optimizations could be implemented in practice. Wind power deployment is largely driven by decentralized and private investment decisions, and coordinated planning across national boundaries poses considerable institutional and political challenges.

One strength of this approach is that it relies solely on measured data. As such, the observed outcomes reflect the actual variability and characteristics of the power system during the period in question, including both planned and unplanned events. Within the limits of data resolution, accuracy, and scope, the method captures realistic conditions without additional modeling assumptions.

Furthermore, the same approach could be extended to other types of generation, or to study marginal effects when additional capacity is introduced or removed from an existing system. These directions may be useful for future research, particularly in the context of mixed technology portfolios or systems undergoing transitions toward higher shares of renewable energy.

## VI. Conclusions

This study explored the intrinsic capacity credit of wind power across a set of twelve European countries, based on measured hourly data for the years 2019 and 2024. The analysis was conducted under the assumption that wind generation would be the sole source of supply, allowing for a direct assessment of how reliably it could meet demand without additional system support.

The results showed significant variation in capacity credit values among countries, with consistently higher values obtained when production was aggregated across the entire region. This is consistent with the notion that spatial diversification can help mitigate the intermittency of wind generation.

A nonlinear regression model was fitted to describe the relationship between capacity credit and default probability. While the model provided a good empirical fit, its similarity to previously observed structures in reserve-related studies remains unexplained and may be a subject of future investigation.


Dubravko Sabolić, Igor Ivanković, Empirical Assessment of Wind Power's Capacity Credit: A European Case Study, Journal of Energy, vol. 74 Number 1 (2025), 3–8
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Additionally, hypothetical spatial redistributions of installed capacity were evaluated using several statistical optimization criteria. These scenarios produced improved adequacy outcomes compared to the actual capacity distribution, although their practical implementation would likely face considerable challenges.

This provides a foundation for potential extensions, such as analyzing mixed technology portfolios or assessing marginal contributions of additional capacity under different system configurations.

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