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Enhancing Photovoltaic Farm Capacity Estimation: A Comprehensive Analysis with a Novel Approach

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This research paper addresses the inaccuracies in the current methods for estimating the capacity value of photovoltaic (PV) plants, which rely heavily on large-scale data and fail to represent the actual capacity value pattern accurately. The research conducts case studies in Belgium, Texas, and California to analyze the impact of different factors on capacity value. It proposes a new metric called the Marginal Moving-Average Limited-Hours (MMALH) Equivalent Load-Carring Capability (ELCC) - Based capacity value. The proposed metric reduces the dependence on hourly data and better represents capacity value. The results from real case studies validate the effectiveness of the new metric, highlighting its novelty and contribution to the assessment of capacity value in PV power systems. The study emphasizes the importance of accurately assessing the capacity value of PV compared to conventional units, considering environmental factors and system parameters. The study exposes the shortcomings in current metrics and advocates for the MMALH ELCC methodology as a more precise evaluation approach. The research suggests optimizing design, employing advanced tracking systems, enhancing maintenance practices, and ensuring effective grid integration to boost solar plant efficiency. Consistent monitoring and analysis of the utilization factor are vital for pinpointing improvement areas and augmenting productivity.

1. Introduction

Stable power system operations rely on three key factors: reliability, adequacy, and security: 1) reliability: this term concerns the consistent supply of electricity; it ensures that power is delivered without interruptions, providing a dependable service; 2) adequacy: adequacy ensures that the power system has ample resources and capacity to meet electricity demand under normal circumstances and unexpected situations, such as equipment failures or emergencies; it's about having a safety net in place; and 3) security: security involves protecting the power system from potential failures or blackouts; it encompasses strategies and measures to prevent issues from occurring and to minimize their impact if they do.

As a result, power system planners and operators must continually refine their approaches to maintain the required reliability, adequacy, and security levels. These aspects are vital for ensuring uninterrupted power supply. The concept of "capacity value" plays a pivotal role in addressing these challenges, especially when integrating renewable energy sources into the power system. Capacity value helps evaluate how effectively renewable sources can contribute to reliability, adequacy, and security. Consequently, it's indispensable for successfully incorporating renewables.[1]

The worldwide energy sector is witnessing incremental rises in electricity consumption, with an annual growth of a few percentage points.[2,3] Concurrently, the photovoltaic (PV) sector experiences substantial annual expansion.[4] The significance of PV power in sustainable energy solutions has underscored the critical importance of accurately estimating its capacity value for effective integration into power systems. However, current estimation methods are prone to significant errors due to various factors such as data granularity, forecasting inaccuracies, and the variability and intermittency inherent in solar energy.[5]

Inconsistencies in the methodologies used to calculate capacity value can lead to divergent outcomes. These inconsistencies highlight the pressing need for precise estimation to optimize resource allocation, enhance grid resilience, reduce greenhouse gas emissions, and facilitate the transition toward a sustainable energy future.[1] The successful integration of PV modules into

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clean electricity generation hinges on precisely evaluating their operational efficiency, a critical factor for gauging their capacity to generate energy.[6] Integrating variable renewable energy sources, like PV power, into the grid presents challenges, notably in accurately estimating capacity value. Various methodologies have been explored, with data quality playing a pivotal role. Research has also delved into innovative techniques, including integrating energy-storage and hybrid renewable systems, such as coupling PV with battery storage.[7]

Research efforts have examined the influence of climate change, regulatory policies, forecasting improvements, and the application of machine learning and artificial intelligence (AI) in capacity value estimation for renewables.[8] Additionally, probabilistic forecasting has emerged as a valuable approach for PV power forecasting, offering a range of possible outcomes instead of a single-point prediction.[9] Combined with machine-learning, metaheuristic optimization techniques can enhance the accuracy of PV power forecasting models and capacity value estimates by fine-tuning model parameters to minimize prediction errors.[10] The research[11] aims to provide policymakers and energy experts with a streamlined approach to designing solar farms, addressing the imperative for renewable energy in urban areas. Long-term planning for solar PV should align with diverse stakeholder goals. Costa et al.[12] proposes a robust optimization strategy to optimize the financial surplus between solar PV producers and consumers, considering uncertainties and stakeholder actions. Using Singapore as a case study, the article highlights the necessity of incentives to meet national solar PV installation targets, cautioning against potential overestimation (20%–30%) without proper planning.

Recent research has expanded capacity value assessment from individual power plants to a holistic evaluation of renewable sources in the power system, considering the system-wide capacity value and the importance of grid flexibility. Moreover, capacity value now includes other energy services renewables provide, such as ancillary services.[13]

The coupling of photovoltaics with energy-storage technologies, particularly battery systems, has shown promise in improving the capacity value of PV power plants. Energy storage helps smooth out the variability and intermittency of PV power, increasing its reliability and, consequently, its capacity value.[14] The potential of hybrid renewable systems, such as solar wind storage, has also been explored. These systems utilize the complementary nature of renewable resources and storage technologies to enhance overall system reliability and capacity value.[7]

Another critical factor is the quality of solar resource data used in capacity value calculations. High-quality data leads to more accurate capacity value estimations, enhancing system planning and operations.[15] Climate change's impact on renewable energy availability patterns is also a significant consideration, requiring integration into capacity value estimation for robust power system planning.[16]

Accurate forecasting plays a crucial role in enhancing the capacity value of renewable energy sources. Machine learning and AI applications are increasingly important in renewable energy forecasting, leading to more efficient system operations.[17]

A broader, system-wide perspective in capacity value assessment has gained traction. This approach considers the combined impact of multiple renewable sources on system reliability, providing a holistic assessment of their capacity value.[18] Capacity value extends beyond electricity production, including ancillary services crucial for maintaining power system stability, such as frequency regulation and voltage support.[19]

The growing adoption of battery-energy-storage systems coupled with solar photovoltaic plants and their potential as dispatchable energy resources and alternatives to conventional peaking generation are examined in ref.[20] while considering their limitations and capacity saturation at high penetrations. This study also compares the value of conventional thermal generators with PV plants. Therefore, the capacity value of renewable energy sources, particularly PV power, is a critical factor in their integration into the power grid.

To further extend the current literature, this study delves into an extensive comparative analysis of six methods for calculating capacity value, including exact and approximate ones. This research does not merely provide a comparative analysis but dissects each method under diverse geographical scenarios, thereby unearthing the unique merits and limitations. This comprehensive approach to analysis offers valuable insights for future research and practical applications, enhancing the understanding of the intricacies associated with these methods and promoting their appropriate use in various scenarios. The research is conducted on a well-established test system and investigates three real-case locations: Belgium, Texas, and California.

Gopi et al.[21] compared various machine-learning approaches for forecasting solar farm performance and investigated how weather affects solar farm performance. Incorporating the study into the literature review would underscore the application of machine-learning techniques in capacity value prediction and offer insights into the impact of meteorological conditions on PV generation. Bi et al.[22] investigate how power is generated by colocated offshore wind and floating solar farms during high wind and wave conditions. Simulations consider several variables and their interactions to predict the stability of solar power generation. Since the electricity generation changes very little, the results validate the feasibility of hybrid offshore wind–solar farms when structural safety is considered. Narasimman et al.[23] used artificial neural networks to examine a 5 MW solar PV system. Levenberg–Marquardt's model performance was satisfactory. The plant's energy usage, shading losses, and performance under various circumstances were all investigated. Power reductions and enhanced performance were attained through optimized tilt angles and appropriate supply management. Power growth is enhanced with regular cleaning.

The study also introduces a novel metric called the "Marginal Moving Average Limited Hours ELCC (Equivalent Load Carrying Capability) - Based Capacity Value (MMALH)." This metric aims to address challenges in estimating the capacity value of PV plants, including data granularity, forecasting, variability, intermittency, and inconsistencies in methodologies. The marginal moving-average limited hours (MMALHs) method leverages a restricted number of hours and employs a moving average approach, improving precision and facilitating better modeling of PV-generation behavior. This novel approach provides a more reliable measure of PV plants' capacity value and effectively reduces errors associated with traditional capacity value estimation methods.

To comprehensively analyze capacity value assessment methods, this study implements case studies examining three real-world locations— Belgium, Texas, and California. The case studies rely on actual solar production data from PV farms in these regions and established reliability test systems for the load profiles. The generation system model includes conventional power plants with a defined capacity. Various capacity value estimation techniques are then applied, including accurate methods like equivalent load-carrying capability (ELCC) and approximation methods like the capacity factor approach. The results are carefully analyzed to discern the effectiveness of different techniques across the diverse geographical scenarios encompassed in the case studies.

A comprehensive examination of prevalent techniques for estimating the capacity value of PV plants underscores distinct advantages and limitations, laying the groundwork for developing innovative approaches. Established methods such as ECP, equivalent firm power (EFP), and ELCC excel in delivering accurate capacity value assessments but are hindered by their reliance on extensive data inputs and complex modeling. In contrast, while computationally simpler, approximation techniques like Garver, Z, and capacity factor suffer from a lack of precision and struggle to capture the variability inherent in PV generation.

Our proposed MMALH ELCC methodology is positioned as a transformative advancement in this landscape. It is designed to strike a delicate balance between the precision of reliability-based methods and the computational efficiency of approximation techniques. By strategically selecting representative hours, MMALH minimizes the demand for extensive datasets, reducing data dependence and computational complexity. Incorporating a marginal capacity value calculation ensures accuracy, while integrating a moving average approach accounts for the variable nature of PV-generation patterns. In this way, MMALH not only addresses the limitations inherent in existing methods but also represents a significant contribution to the field of capacity value prediction for PV plants. This heightened clarity regarding the unique attributes of MMALH not only enhances the critical analysis in the literature review but also underscores our work's novel and substantial contributions, providing a more explicit justification for the study.

The article is structured as follows. 1) Introduction: an overview of the capacity value of power plants, with a focus on PV systems; 2) Capacity Value Methods: various existing methods for determining power plant capacity value are presented; 3) Evaluation of Existing Methods: comprehensive evaluation of existing methods through several scenarios and reporting the significant findings and the shortcomings of existing methods; 4) Proposed Metric: introduction of a new metric for capacity value; 5) Effectiveness Evaluation: evaluation of the effectiveness and superiority of the proposed metric; and 6) Conclusion: a concluding section summarizing the article's key findings and implications.

2. Various Methods of Power Plant Capacity Value

2.1. Problem Definition

The capacity value of renewable energy power units, including PV, is essential for evaluating their contribution to system reliability. Various methods have been proposed to estimate capacity value, with outcomes ranging from 5% to 95% of maximum generation capacity.[1] This wide variance in results highlights a key challenge with existing capacity value calculation techniques. While accurate methods like ELCC provide detailed reliability information, their extensive data requirements lead to impractical implementation complexity. Approximation methods like Garver and *Z* enable more straightforward computation but lack precision in modeling variable PV generation. These deficiencies motivate the development of an enhanced PV capacity value estimation approach that balances accuracy and practical application. Therefore, the critical limitations in the existing capacity value metrics are as follows: 1) high data dependence: methods like ELCC, ECP, and EFP provide accurate assessment but require extensive input data (e.g., hourly generation profiles), leading to impractical complexity in large systems; 2) inability to capture variable PV patterns: approximation techniques like the Garver, Z method, and capacity factor (CF) offer computational simplicity but lack precision in modeling the variable and intermittent nature of PV generation; 3) forecasting inaccuracies: reliability indices used for capacity value calculation depend heavily on forecasted PV-generation data; however, uncertainties and errors in forecasting PV output lead to incorrect capacity value estimates; and 4) inconsistent capacity value evolution: existing methods fail to accurately represent the marginal capacity value contribution decrease as more PV capacity is added to the system.

Overall, limitations in prevailing capacity value estimation methods, including substantial data needs, forecasting inaccuracies, and the inability to capture dynamic PV-generation patterns, lead to significant errors and inconsistencies. This underscores the need for a refined calculation technique that overcomes these challenges to support successful PV integration. The following subsections present the most popular methods in the literature for evaluating the capacity value.

2.2. Accurate Methods

The most commonly used indicators for evaluating the reliability of a power system are the loss of load expectation (LOLE) and loss of load probability (LOLP), which characterize the probability of load shedding due to the possible outage of a portion of the generation capacity. They are directly related to the capacity value of the power units. Based on these indicators, three main methods have been proposed for determining the capacity value of photovoltaic power units.

2.2.1. ELCC Method

The ELCC represents the allowable increase in the load level that can be added to the system without changing the LOLE value when adding a new power unit. To calculate the ELCC corresponding to a PV power unit, the LOLP value without considering the PV unit is calculated using Equation (1):[24]

$$\varepsilon = \sum_{t \in T} p_t = \sum_{t \in T} \mathrm{Prob}\{G_t < L_t\} \tag{1}$$

Then, the PV unit is added to the system. Considering the variable generation of the PV unit in each hour, it is necessary to rewrite the capacity outage probability table (COPT) for each hour. By considering these changes and adding a constant load to the entire load profile, the new LOLE value of the system is calculated using Equation (2):[9]

$$\varepsilon^{\mathrm{ELCC}} = \sum_{t \in T} \mathrm{Prob}\{G_t + V_t < L_t + \overline{L}\} \tag{2}$$

By changing the constant load added to the load profile ($\overline{L}$) in an iterative process, the constant load value that satisfies Equation (3) can be obtained:

$$\varepsilon^{\mathrm{ELCC}} = \varepsilon \tag{3}$$

Therefore, the capacity value of the PV power unit is equal to the load value ($\overline{L}$) resulting from Equation (3). It should be noted that by considering the variable generation of the PV unit, the uncertainty of solar irradiance is also somewhat included in the presented model, using multiyear data.[25]

2.2.2. Equivalent Conventional Power (ECP) Method

The ECP of a power unit is the capacity of a conventional power unit with a defined forced outage rate (FOR) that, if replaced by a new power unit, will not change the LOLE value.[26] To calculate the LOLE value with the addition of a PV unit to the system, Equation (4) is calculated:

$$\varepsilon^{\mathrm{PV}} = \sum_{t \in T} \mathrm{Prob}\{G_t + V_t < L_t\} \tag{4}$$

Then, the PV unit is replaced with a benchmark unit with an FOR rate of 5%. The LOLE value is recalculated using Equation (5):

$$\varepsilon^{\mathrm{B}} = \sum_{t \in T} \mathrm{Prob}\{G_t + B_t < L_t\} \tag{5}$$

The nominal capacity of the benchmark unit (B_t) is then changed in an iterative process to satisfy Equation (6):

$$\varepsilon^{\mathrm{PV}} = \varepsilon^{\mathrm{B}} \tag{6}$$

The capacity value of the PV power unit based on the ECP measure is equal to the nominal capacity of the benchmark unit.[26]

2.2.3. Equivalent Firm Power (EFP) Method

This method is very similar to the ECP method but has a zero FOR value for the benchmark unit. Therefore, the PV power unit is always replaced with an entirely ideal power unit available at all times.[27]

2.3. Approximation Methods

As the dimensions of the power system increase, exact methods become very time-consuming, and they also require a large database to increase their accuracy. Therefore, approximation methods that use less data and reach a solution faster have been proposed. The following three common methods are generally used.

2.3.1. CF Approximation

In this method, the capacity value of a PV unit is approximated by the average capacity factor or CF of that unit in high-risk intervals. These high-risk intervals can be high LOLP intervals by considering the generation system without PV or high load intervals. The standard average CF value can be calculated, or a weighted average, to give a higher value to the CF for higher-risk hours. Here, we use the weighted average method. To do this, the subinterval T' is first selected where the system load is high, and in these intervals, the value of LOLP is determined. Then, weighted coefficients are calculated for all study hours according to Equation (7)[28]:

$$w_t = \frac{p_t}{\sum_{\tau \in T'} p_\tau} \tag{7}$$

With the aforementioned weighting coefficients, the capacity value of the PV unit is obtained from Equation (8).

$$\sum_{\tau \in T'} w_\tau V_\tau \tag{8}$$

2.3.2. Garver Approximation Method

Garver has provided an approximation for the LOLP function in which the LOLP function is approximated by an exponential function with two parameters, β and γ.[29] As a result, the value of LOLE for the system without considering the PV unit can be calculated with Garver approximation as Equation (9):

$$\varepsilon \approx \sum_{t \in T} \beta.\exp\left(-\frac{\overline{G} - L_t}{\gamma}\right) \tag{9}$$

Now, if the PV unit is added to the generation system and a constant load is also added to the entire load profile, the value of LOLE with Garver approximation is obtained from Equation (10):

$$\varepsilon^{\mathrm{ELCC}} \approx \sum_{t \in T} \beta.\exp\left(-\frac{\overline{G} + V_t - L_t - \overline{L}}{\gamma}\right) \tag{10}$$

As mentioned in the ELCC-based method, the capacity value of the PV unit equals a fixed value of load so that the value of LOLE does not change. The fixed load value is calculated from Equation (9) and (10) by setting them equal to each other, as shown in Equation (11):

$$\overline{L} = \gamma.\log\left(\frac{\sum_{t \in T} \exp\left(\frac{L_t}{\gamma}\right)}{\sum_{t \in T} \exp\left(\frac{L_t - V_t}{\gamma}\right)}\right) \tag{11}$$

As a result, the value of the capacity of a PV power plant unit is equal to the calculated load value in Equation (11).

2.3.3. Z Approximation Method

This method focuses on the difference between the available production capacity and the load (reserve value) during peak load hours without considering the PV power plant unit. To explain this method, we first define the reserved parameter as Equation (12):

$$S_t = G_t - L_t \tag{12}$$

In a complex power system featuring multiple power plant units, it is asserted that the variable S_t follows a Gaussian distribution. Moreover, the relationship between the average (mean) and the variability (standard deviation) of S_t serves as a gauge of the system's capacity adequacy, denoted as Z according to Equation (13):

$$Z = -\frac{\mu_S}{\sigma_S} \tag{13}$$

Furthermore, the assertion holds that when augmenting production capacity or introducing additional load into the power system, while the mean and variance values may alter, we still observe a Gaussian distribution in which Z remains unchanged. Consequently, the capacity of a PV power plant unit is equivalent to the load that needs to be incorporated into the system every hour to maintain a consistent value of Z. With the addition of a PV power plant unit and a constant load to the system, the mean and standard deviation values of St change to $\mu_S + \mu_{PV} - \overline{L}$ and $\sqrt{\sigma_S^2 + \sigma_{PV}^2}$, respectively. Therefore, to keep Z constant, Equation (14) must hold

$$-\frac{\mu_S}{\sigma_S} = -\frac{\mu_S + \mu_{PV} - \overline{L}}{\sqrt{\sigma_S^2 + \sigma_{PV}^2}} \tag{14}$$

By solving Equation (14), Equation (15) is obtained:

$$\overline{L} = \mu_{PV} + Z\left(\sqrt{\sigma_S^2 + \sigma_{PV}^2} - \sigma_S\right) \tag{15}$$

Consequently, the capacity of a PV power plant unit aligns with the load calculated in Equation (15). It's important to highlight that this method assumes that the distribution of S_t continues to follow a Gaussian pattern even with the integration of PV units. This approach is applicable for power systems with relatively low levels of PV power plant unit penetration or, in rare instances, when only a single PV power plant unit is introduced into a production system primarily comprising traditional power plant units.

3. Comprehensive Evaluation of Existing Methods

To thoroughly investigate and assess the effectiveness and limitations of the existing methods, it is imperative to explore a range of conditions. Additionally, measuring the influence of diverse conditions and parameters on capacity values is a crucial aspect of this evaluation. Consequently, a set of distinct scenarios has been delineated for this purpose. In the forthcoming subsections, we will scrutinize the test system data and subsequently analyze the numerical outcomes.

3.1. Data

3.1.1. Generation System

The generation system of this network includes traditional power plants with a total production capacity of 3405 MW, and the maintenance schedule is omitted.[30]

3.1.2. PV Power Plant Unit Information

Different scenarios for the PV power plant units have been considered in this project, including production patterns of a sample PV power plant unit in Belgium, Texas, and California, as shown in **Figure 1**.

3.1.3. Independent Load Profile

Regardless of the peak load, which should be selected according to the production capacity, the load profile in different regions differs and will affect the LOLP and capacity value. Therefore, different load profile scenarios are considered here, including reliability test system (RTS), electric reliability council of Texas (ERCOT), and Belgium network load profiles, as shown in **Figure 2**.[31,32] RTS and ERCOT are robust and widely recognized benchmarks for reliability evaluations that were chosen to enhance the credibility of our study. Specifically, ERCOT and RTS were selected for their widespread recognition as reliable benchmarks in the power industry, providing a foundation for comparisons with existing research and industry standards. Moreover, we have also chosen the Belgium load profile due to its significantly different pattern compared to the other load profiles. This deliberate selection was motivated by our aim to comprehensively evaluate the capacity assessment methods under diverse scenarios. Including the Belgium load profile ensures that our study captures a broad spectrum of potential challenges and opportunities. This contributes to a more comprehensive understanding of the capacity values for PV plants in various regional contexts.

In all scenarios, the peak load is 2850 MW, and the capacity of the PV unit is 5 MW with an emergency outage rate of 0.1%. Also, in the capacity factor and Z methods, hours with high risk are selected when the load exceeds 80% of the peak.

3.2. Scenario Generation and Result Analysis

3.2.1. Scenarios Related to Different Environmental and Geographical Conditions and Analysis of the Results of Implementing Different Capacity Valuation Methods

In this section, we have generated five scenarios by selecting various climatic conditions for load and solar production. We then applied different capacity valuation methods to these scenarios, and the results are presented in **Table 1**. 1) When comparing scenarios 1 and 2, it becomes evident that differing solar production patterns notably influence the capacity value of the PV power plant unit despite having the same load profile. Figure 1d illustrates the production pattern of the PV power plant unit in Belgium and Texas. Notably, the PV power plants in Texas

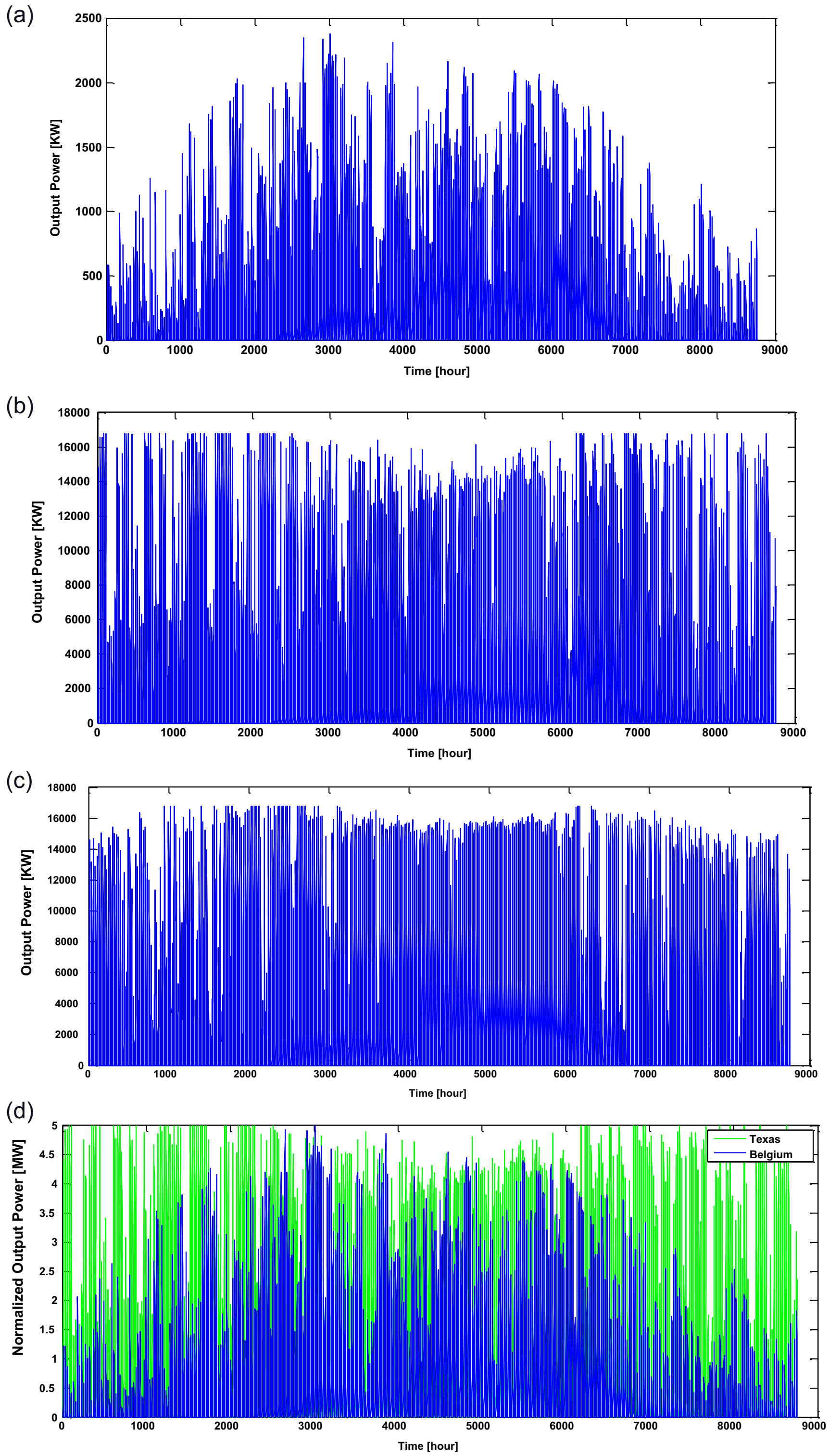

Figure 1. Sample solar production in a) Belgium, b) Texas, c) California, and d) comparison of Belgium and Texas.

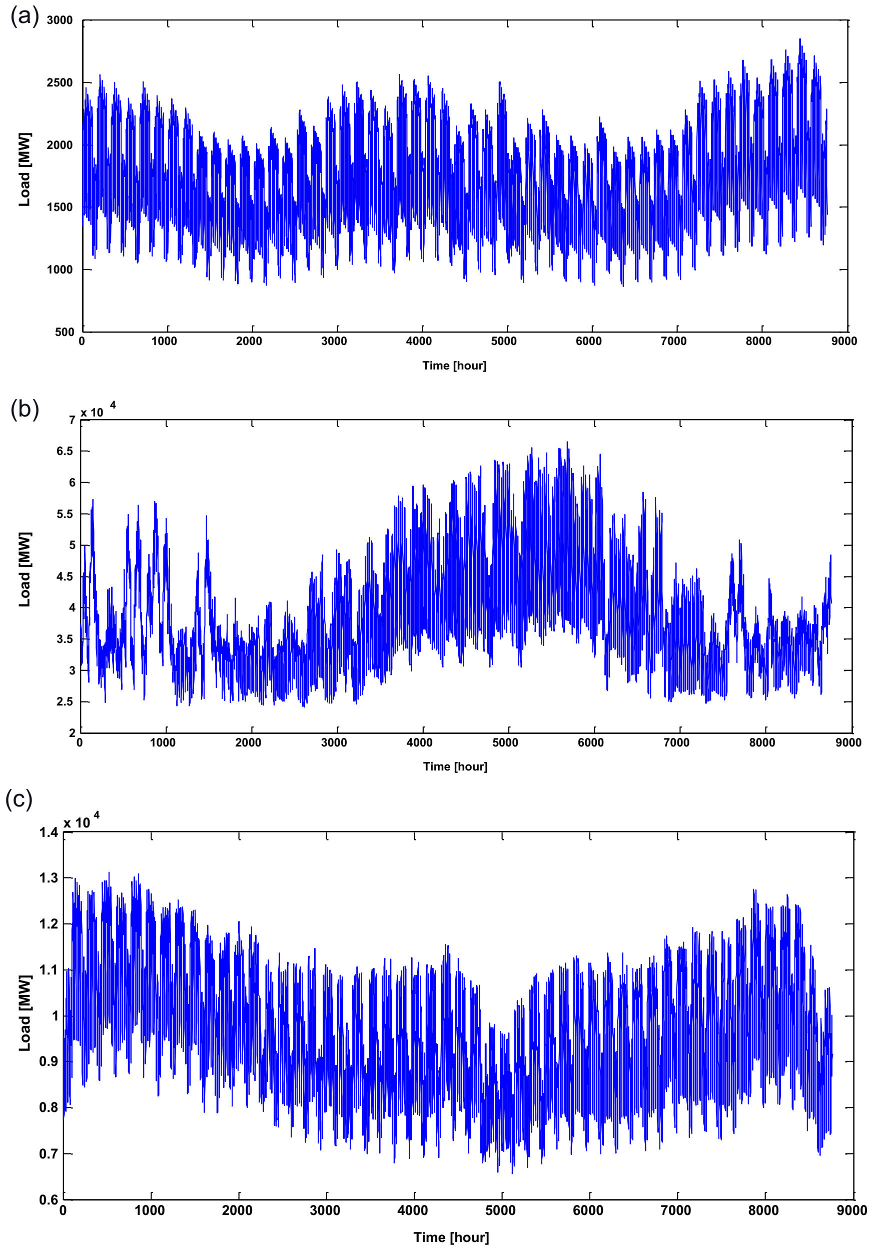

Figure 2. Network load profiles in a) RTS, b) ERCOT, and c) Belgium.

Table 1. Results of implementing different capacity valuation methods for different scenarios related to different load and production conditions for a 5 MW PV power plant.

Scenario	Load	PV	ELCC [MW]	ECP [MW]	EFP [MW]	Capacity factor [MW]	Garver [MW]	*Z* [MW]
1	RTS	Belgium	0.37	0.75	0.7	0.642	0.7371	0.934
2	RTS	Texas	1.18	2.03	1.95	1.5927	1.6035	1.7876
3	Belgium	Belgium	0.74	0.95	0.92	0.6827	0.7146	1.0342
4	ERCOT	Texas	2.13	2.07	1.91	2.4493	2.3137	2.059
5	ERCOT	California	2.3	1.88	1.8	2.4734	2.3653	2.1931

exhibit higher overall production levels, and their production pattern significantly varies from that in Belgium, with more consistent production throughout the year. 2) Although PV power generation in Belgium is relatively modest, a significant capacity value increase is observed when comparing scenarios 1 and 3. This increase is attributed to both scenarios sharing the same PV power generation conditions and geographical region, highlighting the interplay between these factors. 3) Upon examination of all scenarios, it is apparent that most methods exhibit similar behavior, except for scenario 5. In this case, compared to scenario 4, the ECP and EFP methods produce contrasting values. This deviation arises from the distinct calculation techniques employed by these methods. While it is generally expected that reliability-based methods yield similar values, certain load and production patterns can lead to outcome differences due to methodological variations. 4) Across nearly all scenarios, the values obtained from various methods exhibit remarkable consistency with minimal divergence. The exception to this trend is scenario 1, where the ELCC value notably deviates from the values derived through other methods.

3.2.2. The Effect of PV Unit Capacity

In this section, we investigate the impact of PV capacity on its capacity value. To achieve this, we maintain consistent load and PV production conditions while varying only the capacity of the PV unit. This analysis uses the ERCOT load profile and PV production data from Texas, resulting in the creation of the sixth scenario, as detailed in **Table 2**.

Figure 3a presents the outcomes of applying various capacity valuation methods to scenario 6. This graph illustrates how the capacity value of each megawatt (MW) of a PV unit fluctuates in response to changes in the rated capacity of the PV unit. The results demonstrate that approximation methods are not highly affected by changing the rated capacity of PV units, while the

Table 2. Scenario related to analyzing the effect of PV unit capacity on capacity value.

Scenario	Load profile	Maximum load [MW]	PV generation profile	PV unit's FOR [%]	PV rated capacity [MW]
6	ERCOT	2850	Texas	0.1	0.1–10

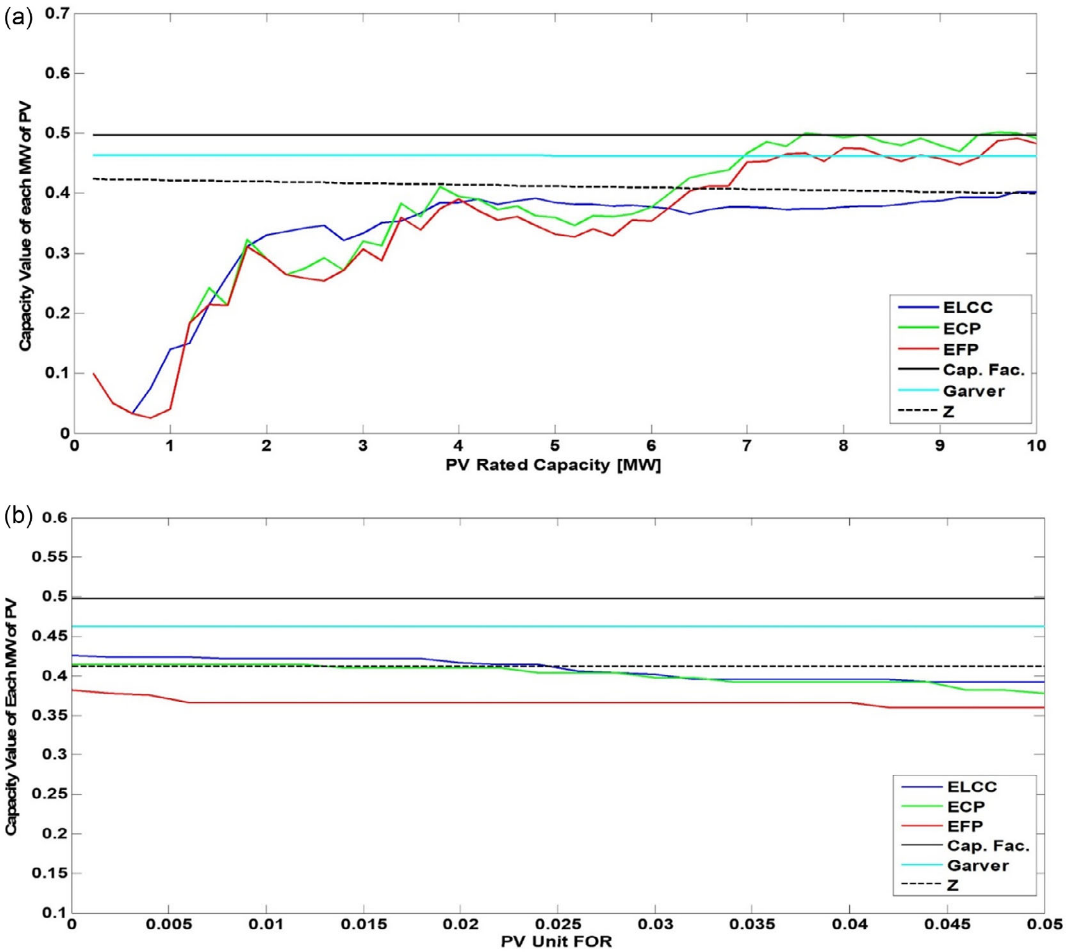

Figure 3. Changes in the value of capacity per megawatt of PV unit with the variation of a) nominal capacity of PV unit and b) the FOR of the PV unit.

exact methods vary significantly. The overall trend of variation in exact methods is increasing with the increment in the rated capacity of PV units. ELCC shows a smoother curve and the capacity value change rate decreases when the rated capacity increases. This can be justified as for a specific range of low values for the rated capacity of PV unit, the capacity value of each MW of PV unit increases as it has a higher effect on the generation system.

3.2.3. The Effect of the PV Unit's FOR

In this section, we maintain the conditions of scenario 6, keeping the PV unit's capacity constant at 5 MW. However, we vary its FOR value to analyze the impact of FOR on its capacity value. This analysis defines the seventh scenario, as detailed in **Table 3**.

The result of implementing different capacity valuation methods for scenario 7 is shown in Figure 3b. As expected, approximation methods are not affected by the FOR of the PV unit, while exact methods show a decreasing trend when the FOR of the PV unit increases.

3.2.4. The Effect of Peak Load

This section investigates how peak load variations affect the PV unit's capacity value. This analysis leads to creating the eighth scenario, outlined in **Table 4**.

The result of implementing different capacity valuation methods for scenario 8 is shown in **Figure 4**a. It is highly expected that the capacity value of the PV unit should increase when the system's peak load increases. In this case, approximation methods show an opposite direction, and therefore, their accuracy when increasing the peak load is significantly low. However, the exact methods show an increasing trend with increasing the system's peak load.

3.2.5. The Effect of Selecting a Peak Period Basis on CF-Based and Z Methods

The objective of this scenario is to assess the impact of choosing a specific peak load period on the accuracy of CF-based and Z methods, both of which rely on calculations made for the peak load period. This examination results in formulating the ninth scenario, as presented in **Table 5**.

By implementing the aforementioned scenario, the changes in CF-based and Z indicators are shown in Figure 4b, where the capacity value with the ELCC indicator is also compared. Exact methods consider all the hours and will not be affected in this scenario. However, as is seen in Figure 4b, tightening the risky period considerably affect the capacity value of approximation methods. It can be understood that as the load profile has a sharper shape around the peak load and as the timing of peak load and peak generation of the PV unit aligns more, the capacity value should increase. However, exact methods cannot accurately consider the significance of peak load periods in capacity value evaluation. This can be considered as one of the limitations of the existing methods.

3.2.6. The Effect of Equipping the PV Unit with a One-Axis and Two-Axis Solar-Tracking System

In this section, we explore the impact of incorporating a solar-tracking system, specifically a one-axis and two-axis tracking system,[7] on the capacity value of the PV unit. Including such a system, which optimizes solar radiation capture and subsequently boosts power generation, is expected to increase capacity value. Consequently, we define the tenth scenario, outlined in **Table 6**, to assess this effect.

The result of implementing different capacity valuation methods for scenario 10 is shown in **Table 7**.

As anticipated, the presence of a solar-tracking system, which enhances the power generation of a PV unit, indeed leads to an increase in the unit's capacity value. This augmentation in capacity value is observed consistently across all six accurate and approximation methods.

3.3. Effect of Rated Capacity on Capacity Value

In this subsection, we investigate the impact of adding a new PV unit to the generation system on its capacity value. To isolate the effect of the unit's capacity from the variability of PV generation, we employ scenario 2 within the RTS system, which has an installed generation capacity of 3405 MW and a yearly peak load of 2850 MW. The PV generation pattern for Texas has been deliberately modified to create a smoother and more stable generation profile. To mitigate the influence of variability on this study, we've narrowed the maximum difference between peak and valley generation to 10%. Additionally, we have chosen to use ELCC to assess the units' capacity value for this analysis.

Table 3. Scenario related to analyzing the effect of PV unit's FOR on capacity value.

Scenario	Load profile	Maximum load [MW]	PV generation profile	PV unit's FOR [%]	PV rated capacity [MW]
7	ERCOT	2850	Texas	0–5	5

Table 4. Scenario related to analyzing the effect of peak load amount on capacity value.

Scenario	Load profile	Maximum load [MW]	PV generation profile	PV unit's FOR [%]	PV rated capacity [MW]
8	ERCOT	2750–3350	Texas	0.1	5

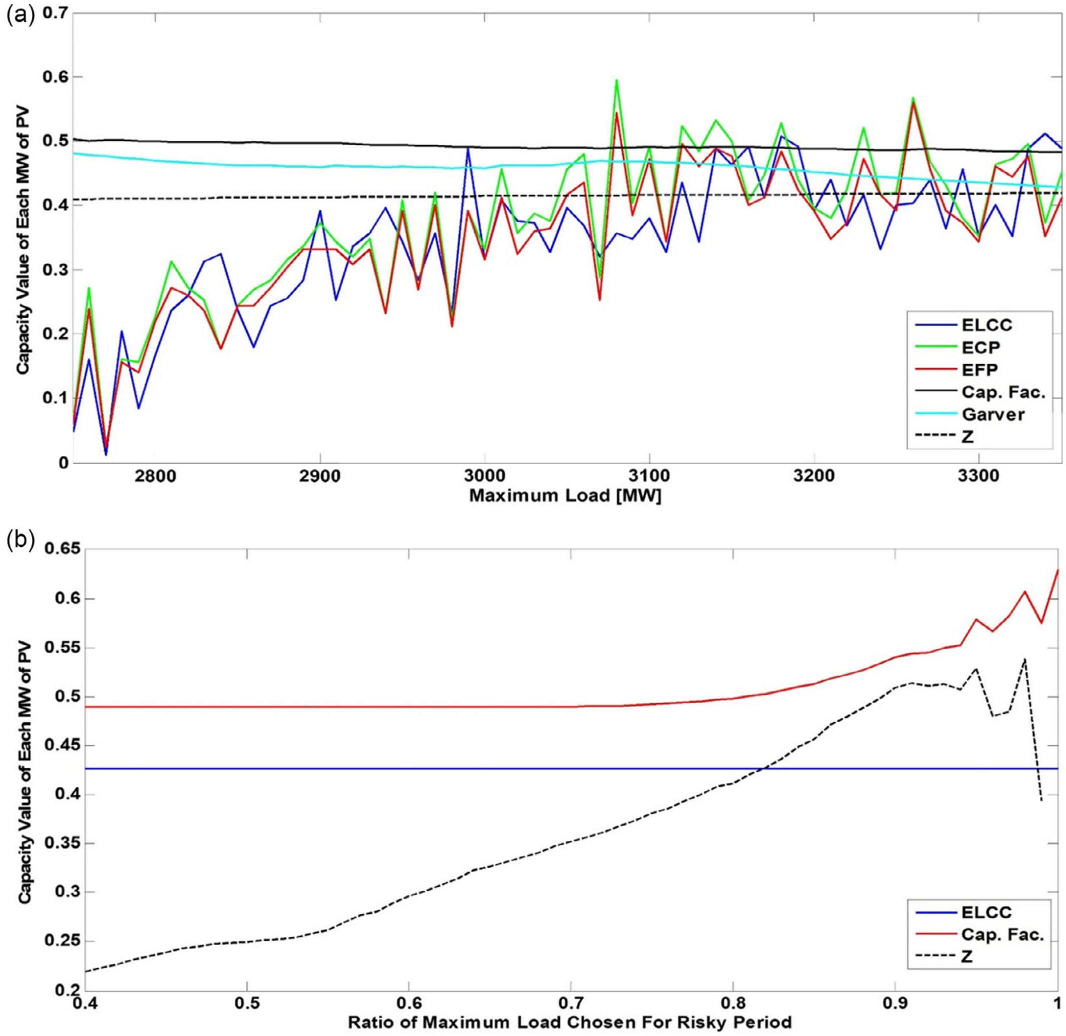

Figure 4. Changes in the value of capacity per megawatt of PV unit with the variation of a) peak load and b) the high-risk period.

Table 5. Scenario related to analyzing the effect of selecting a high-risk period on capacity value.

Scenario	Load profile	Maximum load [MW]	PV generation profile	PV unit'[s] FOR [%]	PV rated capacity [MW]	Risky time (% of maximum load)
9	ERCOT	2850	Texas	0.1	5	40–100

Table 6. Scenario related to analyzing the effect of the presence of a solar-tracking system on capacity value.

Scenario	Load profile	Maximum load [MW]	PV generation profile	PV unit's FOR [%]	PV rated capacity [MW]	Risky time (% of maximum load)
10	ERCOT	2850	Texas, fixed, one-axis & 2-axis	0.1	5	80

Table 7. Results of implementing different capacity valuation methods for scenario 10.

Sun-tracking system	ELCC	ECP	EFP	CF	Garver
Fixed	2.13	2.07	1.91	2.4493	2.3137
One-axis	2.96	3.19	3.08	3.1136	2.9387
Two-axis	3.15	3.33	3.25	3.2512	3.0717

3.3.1. Increasing the Capacity as Independent Units

In this section, we systematically adjust the capacity of the new unit being introduced to the system and calculate the capacity value for each MW of capacity. This measurement is expressed as a per-unit ratio of capacity value to capacity. By analyzing the variations in the capacity value, we aim to discern the influence of the unit's capacity on its capacity value. This study is driven by the primary objective of understanding how the unit's capacity level impacts its capacity value.

Changes with Variable Steps and a Wide Range of Values: The changes, with the unit capacity varying from 0.1 to 5000 MW, are illustrated in **Figure 5**. The main difference between this analysis and scenario 6 is that in this scenario, we increased the range of variation for the rated capacity to see how the capacity evaluation methods behave with high variation of rated capacity.

As observed, the per-MW value undergoes distinct trends as the capacity of the new unit is considered as a percentage of the existing system capacity: 1) 0.003%–0.03% of the system capacity: a substantial increase in the per-MW value with a steep slope is evident; 2) 0.03%–0.14% of the system capacity: the increase in per-MW value continues, albeit with a more gradual slope; 3) 0.14%–20.55% of the system capacity: the per-MW value remains relatively stable during this range; 4) 20.55%–73.4% of the system capacity: a decline in the per-MW value is observed; this behavior aligns with the expectation for decreasing the capacity value when the rated capacity increases to very high values than the maximum load of the system; and 5) 73.4%–146% of the system capacity: in this range, a gradual slope characterizes a slight upturn in the per-MW value; the slight increment in the capacity value differs from our expectation, and this phenomenon can be considered another limitation of existing methods.

Changes with Fixed Steps and a Limited Range of Values: Given that adding units with extremely low capacities (0.1 MW) or units with capacities close to the existing system capacity is not practically feasible, we will refine our study by focusing on a more practical capacity range. To simplify our analysis, we will consider fixed increments in capacity. Specifically, we will investigate the capacity range of the PV unit from 1 to 100 MW, exploring three distinct scenarios with different step changes in capacity, as seen in **Figure 6**.

3.3.2. Adding Sequentially New Units

This section will implement a different approach when adding new units to the system. For instance, when adding a 10 MW unit, we will do so by sequentially incorporating 1 MW units and measuring the capacity value for each of these newly added 1 MW units. Subsequently, we will examine various scenarios involving the addition of a 100 MW unit, considering increments of 1, 2, and 5 MW.

This approach allows us to gain insights into the capacity value at various stages of capacity addition, offering a more granular understanding of how different unit sizes affect the outcome.

The following graphs are obtained for these scenarios (**Figure 7**).

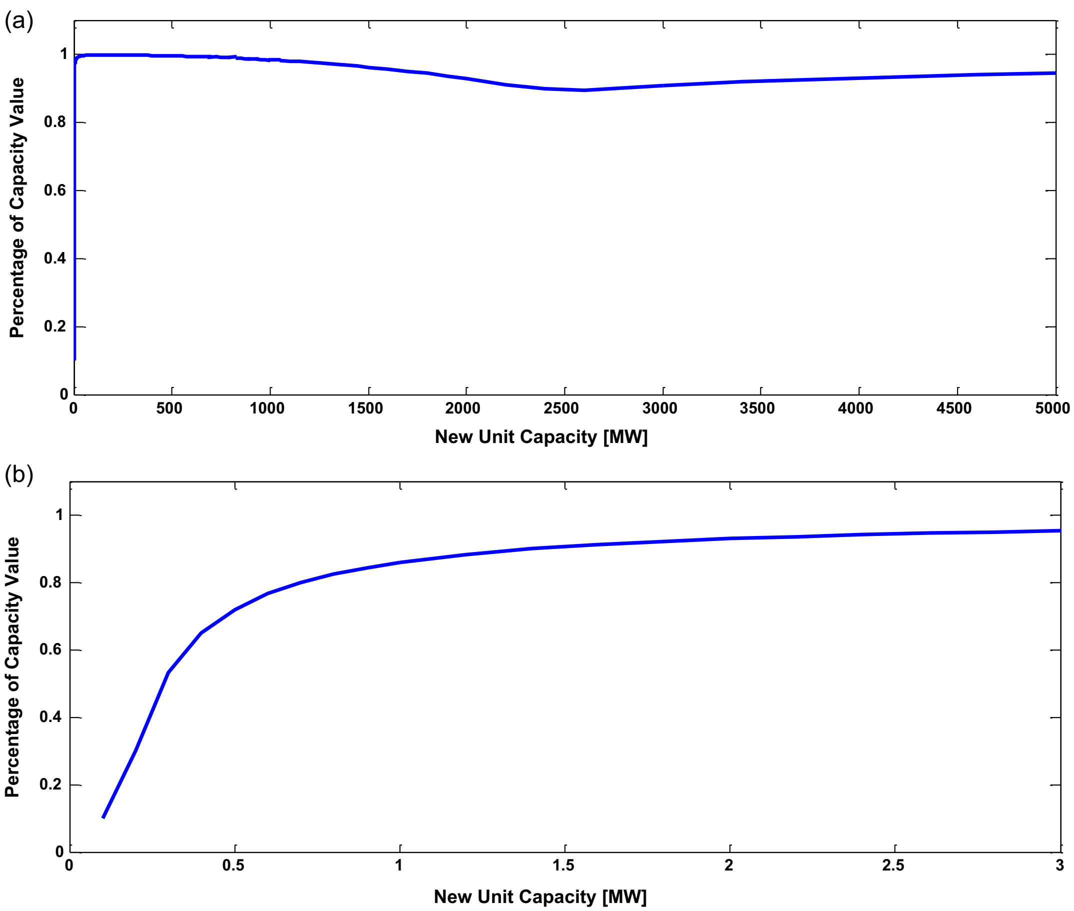

Figure 5. Changes in the value of each MW of capacity as the new unit capacity increases with variable steps: a) a general view and b) the initial changes.

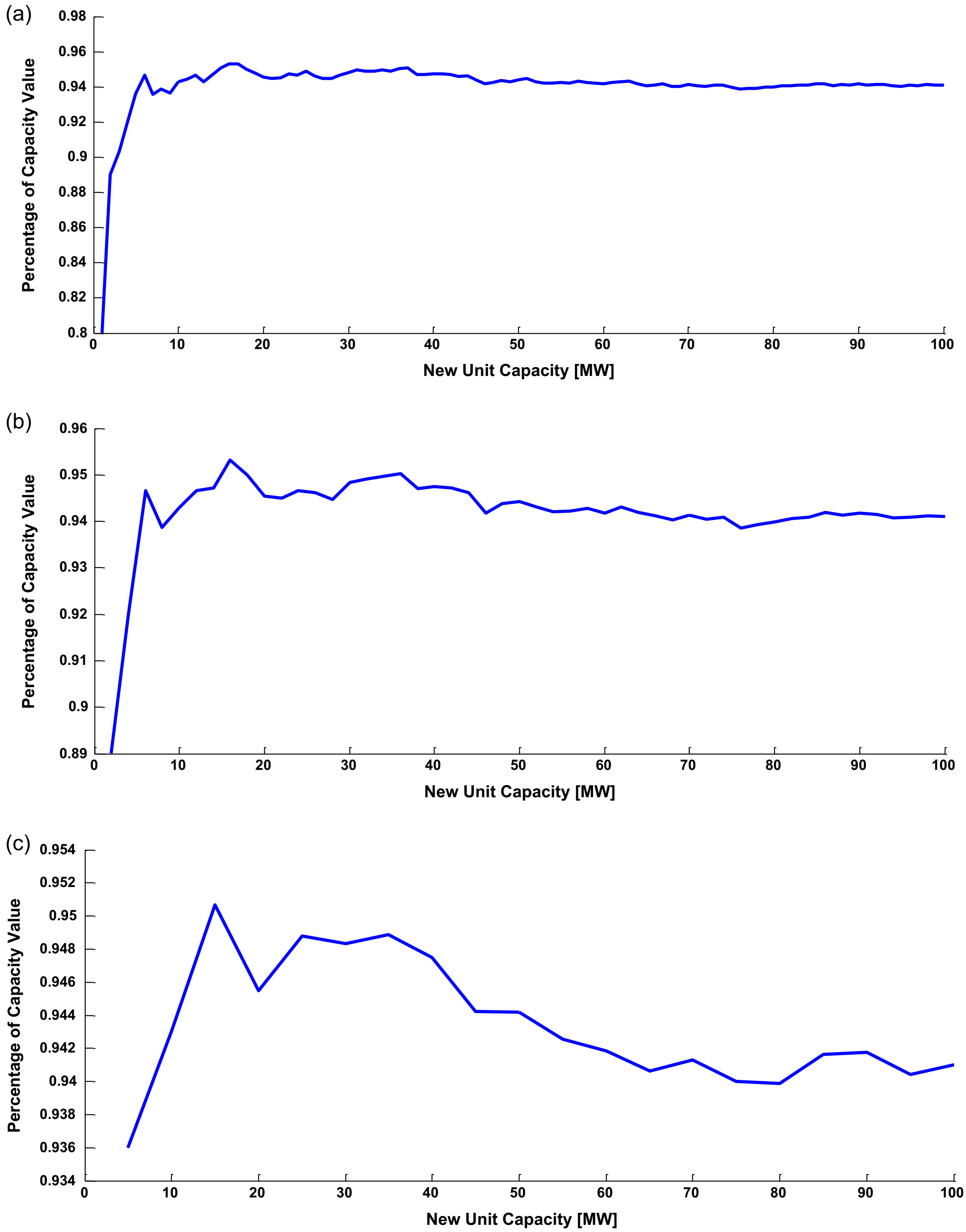

Figure 6. The changes in the capacity value of each MW of capacity as the new unit capacity increases with a) 1 MW step, b) 2 MW step, and c) 5 MW step.

Figure 7 demonstrates that the overall trend of capacity value variation with adding new units to the generation system is decreasing. It is justifiable that as new units are added to the generation system, the need to have more generation capacity to satisfy the demand with acceptable reliability decreases. Therefore, the capacity value should also decrease. However, we can see that high fluctuations also exist in the trends in Figure 7, which are more than expected. This behavior is another limitation and shortcoming of the existing methods.

3.4. Discussion and Limitations

In Section 3, we comprehensively evaluated different scenarios to demonstrate how the capacity value using existing methods changes in response to variations in different parameters of the system, including the rated capacity of the PV unit, the FOR of the PV unit, maximum load of the system, and the risky period of load profile. Several key findings emerged from this analysis, which are described as follows: 1) environmental and

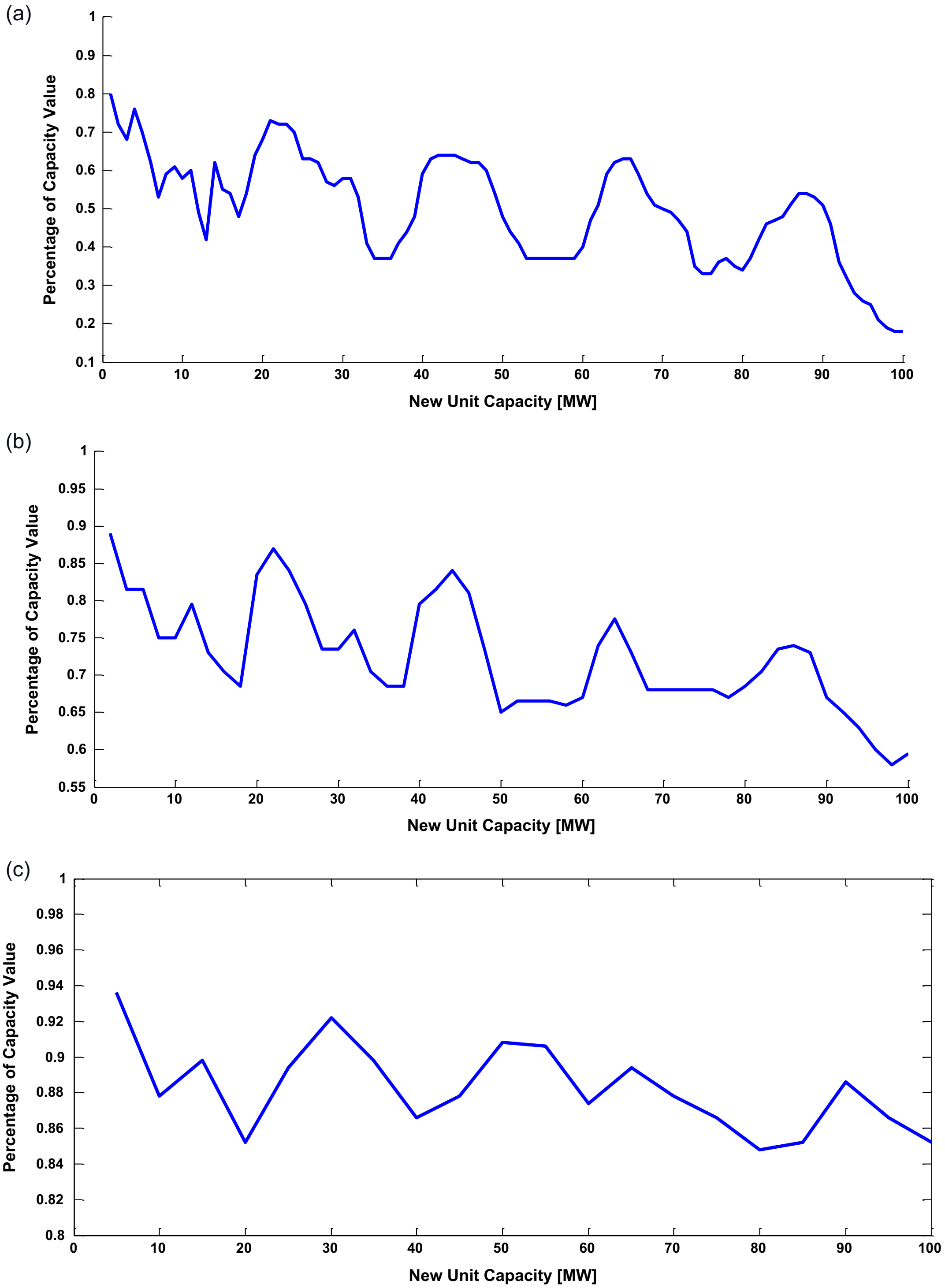

Figure 7. The changes in the capacity value of each MW of capacity as the a) 1 MW, b) 2 MW, and c) 5 MW units are added step by step.

geographical factors: environmental and geographical conditions, such as solar radiation levels and temperature in the region, substantially impact the capacity value of PV units; 2) load profile matching: the degree to which the load profile aligns with the solar radiation pattern significantly influences capacity value; 3) additional parameters: other factors like PV unit capacity, FOR, peak load, and the presence of a solar-tracking system were also investigated; each factor was observed to have a distinct effect on capacity value; 4) comparison with conventional units: generally, it was noted that the capacity value of PV power plant units, even under optimal conditions, tends to be lower than that of conventional units that can consistently achieve their desired production levels; and 5) performance of approximation methods: across different scenarios combining load profiles and PV-generation patterns, approximation methods, which rely on mean and variance values, demonstrated more significant similarity to ELCC than ECP and EFP methods; this resemblance was especially pronounced when the load and PV-generation profiles originated from the same geographical area.

In conclusion, when predicting the capacity value of a PV unit for future generation and load profiles, ELCC exhibited superior performance compared to ECP and EFP, particularly in scenarios where load and PV-generation profiles vary over time. ELCC's ability to account for the dynamic behavior of both load and PV generation makes it a more suitable method for such real-world scenarios.

Moreover, based on the close relationship between the capacity value and reliability indices of the power system, our initial expectation was that increasing the capacity of the new unit should result in increasing the capacity value to reach a peak point and then, for high values of the rated capacity, the capacity value should decrease or remain unchanged as the rated capacity increases. Moreover, gradually adding new capacity to the unit should decrease the overall capacity value. This expectation was based on the rationale that as the overall capacity of the generation system increases, there should be less need for additional generation capacity to meet demand. In essence, when a generation system possesses a capacity significantly exceeding its peak load, adding new units would be a limited necessity. Conversely, in scenarios where the generation system cannot meet demand during outage scenarios, there would be a more significant requirement for additional generation capacity. Consequently, new units in such situations should exhibit a higher capacity value.

These expectations were rooted in the fundamental relationship between capacity and demand within the context of a generation system. However, the actual simulations have yielded results that exhibit more nuanced and complex patterns of change in capacity values under different conditions, as previously described. Therefore, the limitations and shortcomings of the existing methods described in Section 2 are as follows: 1) while approximation methods have less dependency on hourly data and are less prone to forecasting inaccuracy, they are not affected by the rated capacity and the FOR of the PV unit; therefore, exact methods behave better in presenting the variations of capacity value; 2) increasing the rated capacity of the PV unit to high values resulted in the ascending trend of the capacity value, which is one of the shortcomings of the existing exact methods; 3) while existing exact methods demonstrate the overall descending trend of the capacity value when new units are added step by step to the generation system, the fluctuations of the curves are higher than expected, which is another shortcoming of the existing exact methods; 4) existing exact methods cannot accurately reflect the effect of risky periods on the capacity value evaluation of PV units; and 5) data dependency in existing exact methods is high such that all hourly data of the generation and load profile is required to evaluate the capacity value of PV units, which is another limitation of these methods.

4. Proposed New Metric for Capacity Value

Based on our comprehensive analysis and discussions concerning various capacity value estimation methods and their limitations and shortcomings, we propose a new practical capacity value metric that effectively represents the behavior of PV-generation units and their impact on the reliability of the generation system.

To formulate this new metric for capacity value estimation, we need to consider two crucial concepts: 1) forecasting: traditional methods for assessing capacity value rely on calculating reliability indices like LOLP based on the system's hourly generation and load data; however, capacity value serves as a metric to anticipate the future value of a unit intended for addition to the generation system. Given the high uncertainty and variability associated with PV generation, accurately estimating the hourly generation of a PV power plant often results in low accuracy. Consequently, even accurate capacity value estimation techniques can contain inherent inaccuracies due to the challenging task of hourly estimation; and 2) capacity value behavior: as elucidated in previous sections, among the accurate methods, ELCC demonstrates better modeling of the variable behavior of PV generation; however, this method has several shortcomings, as explained in Section 3.4.

Taking these considerations into account, we propose a new capacity value metric that incorporates both forecasting and capacity value behavior, enabling a more accurate representation of the future value of PV-generation units within the generation system. This metric addresses the limitations associated with traditional capacity value estimation methods and provides a more reliable assessment of PV unit contributions to system reliability.

To address the issue of inaccurate forecasting, we propose a method that involves considering a limited number of hours when calculating the capacity value. Instead of analyzing all 8760 h a year, we model each day with 6 h strategically selected to represent different demand and PV-generation conditions. For each of these hours, estimating the maximum, minimum, and average values of demand and PV generation is necessary. This approach results in higher estimation accuracy than estimating all hourly values of demand and PV generation.

Additionally, to align with the second concept and the observed behavior of capacity value, we calculate a unit's marginal moving average capacity value as it is added to the system. This approach enables us to capture the capacity value changes associated with incremental additions of PV units.

Therefore, we propose a novel metric called "Marginal Moving Average Limited Hours ELCC-Based Capacity Value (MMALH)." This metric involves breaking down the rated capacity of a PV unit into smaller increments and then calculating the moving average of the capacity value as these smaller units are progressively added to the generation system. To assess the capacity value at each of these incremental steps, we utilize a modified ELCC method. This approach allows us to obtain a more accurate representation of the capacity value of PV units while considering limited hours and incremental additions.

To calculate the modified ELCC corresponding to a PV power unit, the LOLP value without considering the PV unit is calculated using Equation (16):

$$\overline{\varepsilon} = \sum_{t \in \overline{T}} p_t = \sum_{t \in \overline{T}} \mathrm{Prob}\{G_t < L_t\} \tag{16}$$

where $\overline{T}$ is the subset of hours in which the three off-peak, peak, and average values of the daily demand and the three peak, valley, and average values of the daily PV generation are happening.

Then, the PV unit is added to the system. Considering the variable generation of the PV unit in the three specific hours of a day, it is necessary to rewrite the COPT for each of the six critical hours mentioned earlier. Considering these changes and adding a constant load to the entire load profile, the new LOLE value of the system is calculated using Equation (17).

$$\varepsilon^{\text{Modified ELCC}} = \sum_{t \in \overline{T}} \mathrm{Prob}\{G_t + V_t < L_t + \overline{L}\} \tag{17}$$

changing the constant load added to the load profile ($\overline{L}$) in an iterative process, the constant load value that satisfies Equation (18) can be obtained:

$$\varepsilon^{\text{Modified ELCC}} = \overline{\varepsilon} \tag{18}$$

Therefore, the capacity value of the PV power unit is equal to the load value ($\overline{L}$) resulting from Equation (18). Based on the modified ELCC method proposed here, the flowchart for calculating the MMALH capacity value is shown in **Figure 8**. Based on the proposed flowchart, for each of the smaller units of the original PV unit, the capacity value of adding this unit to the base generation system based on the proposed modified ELCC is evaluated, and the moving average value of the capacity values up to this point is determined as MMALH capacity value. Finally, the ultimate marginal capacity value of adding this unit to the generation system is obtained as Equation (19):

$$\mathrm{MMALH} - \mathrm{CV} = n \times \mathrm{MMALH}_n \tag{19}$$

In Equation (19), the final capacity value of the PV unit is calculated based on its rated capacity.

The MMALH metric has significant practical utility for real-world planning and operation of PV plants. The MMALH approach enables system operators and planners to make better decisions regarding PV expansion and integration by accurately assessing a PV plant's marginal capacity value. For instance, the metric can inform optimal PV siting and sizing to extract maximum capacity value based on geographical factors and load profile alignment. During operations, MMALH provides a tool to assess the impacts of PV-forecasting improvements and predict the capacity value of potential PV additions. This allows balancing PV-penetration levels to maintain adequate system reliability and capacity. The proposed MMALH metric delivers a practical tool for PV plant design, planning, and operations to maximize PV penetration without compromising system security.

In the context of this research article, the MMALHs ELCC-based capacity value is a new metric proposed to estimate the capacity value of PV plants. It considers factors such as generation adequacy, limited operating hours, and moving averages to represent the capacity value pattern accurately. The limitations and challenges faced during the case studies conducted in Belgium, Texas, and California include factors such as data availability, data quality, and the representativeness of the selected

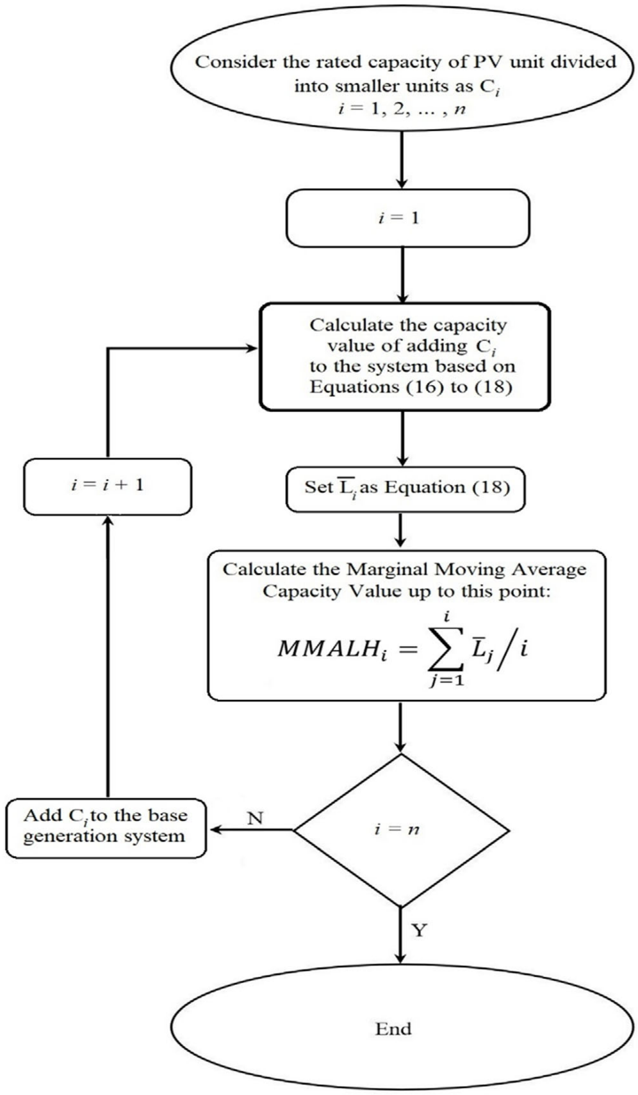

Figure 8. The flowchart of calculating marginal moving average limited-hours capacity value.

locations. In addition to improving capacity value assessment accuracy, the suggested metric clears the path for well-informed decision-making procedures to enable the smooth integration of solar energy into the grid. The advancement of renewable energy is accelerated by the validation of the metric through real-world case studies. By reducing the dependency on fossil fuels, this research contributes significantly to mitigating the adverse effects of climate change and global warming, thereby improving the quality of life on our planet.

5. Effectiveness Evaluation of the Proposed Metric

In this section, we conduct several analyses to evaluate the effectiveness of the new metric proposed in Section 4.

5.1. Comparison with Existing Methods

This analysis compares the capacity value obtained by our proposed and existing methods. The load profile of ERCOT and the PV generation of Texas are considering the specific 6 h of each day in the case study. The PV unit's rated capacity is 10 MW, and a one-axis solar-tracking system is included. The result of comparing the capacity value of this unit is illustrated in **Figure 9**.

Figure 9 illustrates that the result of the proposed metric is very close to other metrics. However, based on the definition of the ELCC approach, the proposed method belongs to the accurate methods category with less dependency on the total hourly data of a year. Therefore, for long-term planning of the power system, it can better estimate the capacity value of a PV unit added to the system. Furthermore, due to the intrinsic nature of this metric, which calculates the marginal moving average capacity value, it is well-suited to effectively capture the trend of capacity value decreasing as the generation system's capacity increases. This aligns with the expected behavior of capacity value as the generation capacity grows.

5.2. Adding a New Unit Gradually and Calculating the Capacity Valueas a Moving Average

In this section, we intend to compare the results obtained in Section 3.3.2 with those from using our proposed metric. To better compare, we use all the hours for calculating Marginal Moving-Average Limited-Hours Capacity Value (MMALH-CV). Therefore, when adding a new unit at each step, we calculate the average capacity value as a moving average. This means we compute and display the average capacity value for the added units up to that point at each step. The results are illustrated in **Figure 10**.

Combining the results using our proposed metric and the results obtained from the existing ELCC method in Section 3.3.2 can better demonstrate the effectiveness of our proposed metric to reflect the descending behavior of capacity value when new units are added sequentially to the generation system. This comparison is demonstrated in **Figure 11**.

To demonstrate the superiority of our proposed MMALH-CV, we also conducted this analysis for 2 MW steps using a limited 6 h daily, as described in Section 4. The result is shown in **Figure 12**.

Figure 12 clearly shows that considering limited hours of the load and generation profile results in a very close capacity value to considering all the hours. Moreover, our proposed MMALH capacity value metric demonstrates a smoother trend in the variation of capacity value, which aligns better with our expectation of having a descending trend for the capacity value when new units are added sequentially to the generation system.

5.3. Increasing the Capacity as Independent Units with a Wide Range

To evaluate the effectiveness of our proposed MMALH-CV compared to the existing methods regarding the second limitation described in Section 4.3, a similar scenario to Section 3.3.1.1 is considered using our proposed method. **Figure 13** demonstrates how the capacity value using MMALH changes when the capacity of the new PV power plant changes from 0.1 to 5000 MW.

Figure 13 demonstrates that our proposed method overcomes the existing method's limitations, and the descending trend continues to happen even for high values of rated capacity.

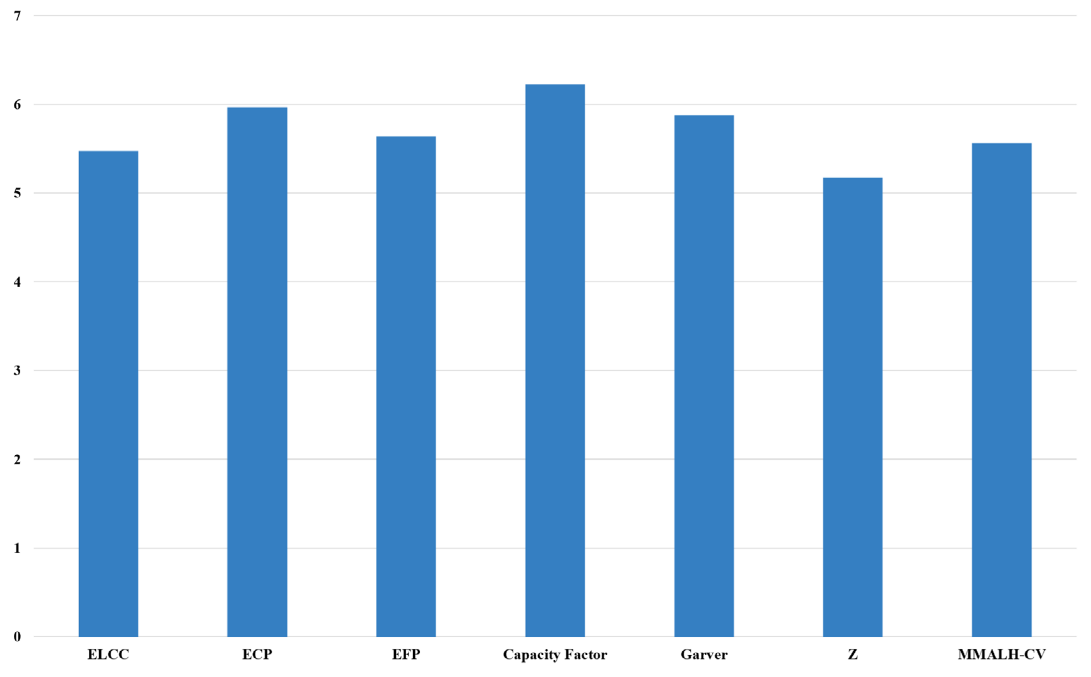

Figure 9. Comparing the results of different metrics for capacity value.

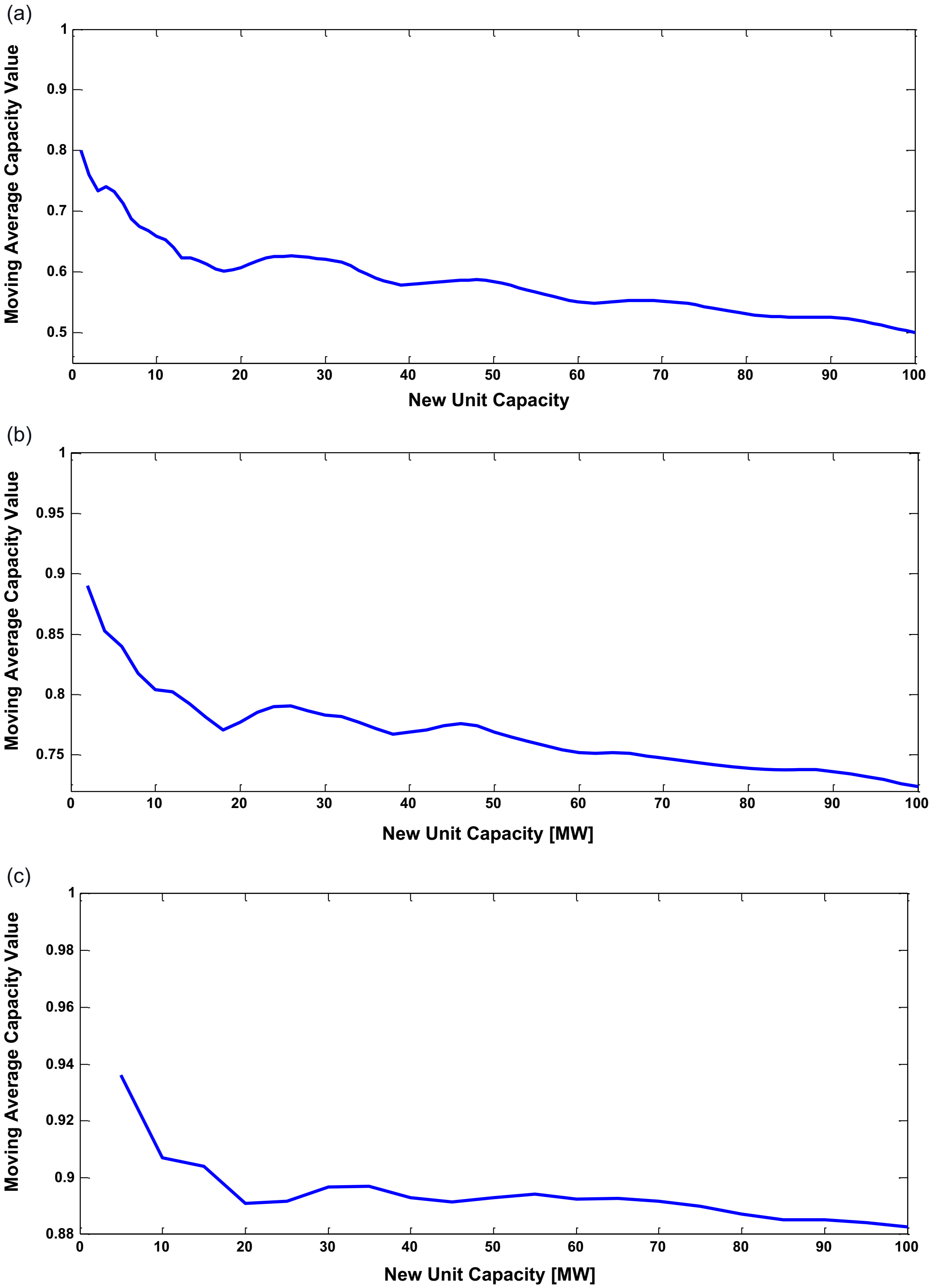

Figure 10. The changes in the moving average capacity value of each MW of capacity as the a) 1 MW, b) 2 MW, and c) 5 MW units are added step by step.

6. Conclusion

This research article comprehensively analyzes existing methods for evaluating the capacity value of PV units and highlights their limitations and shortcomings. The wide variance in results obtained from different methods emphasizes the critical challenge of accurately calculating capacity value. The existing methods either require extensive data and suffer from impractical complexity or approximate the capacity value but fail to capture the variable nature of PV generation. Additionally, forecasting

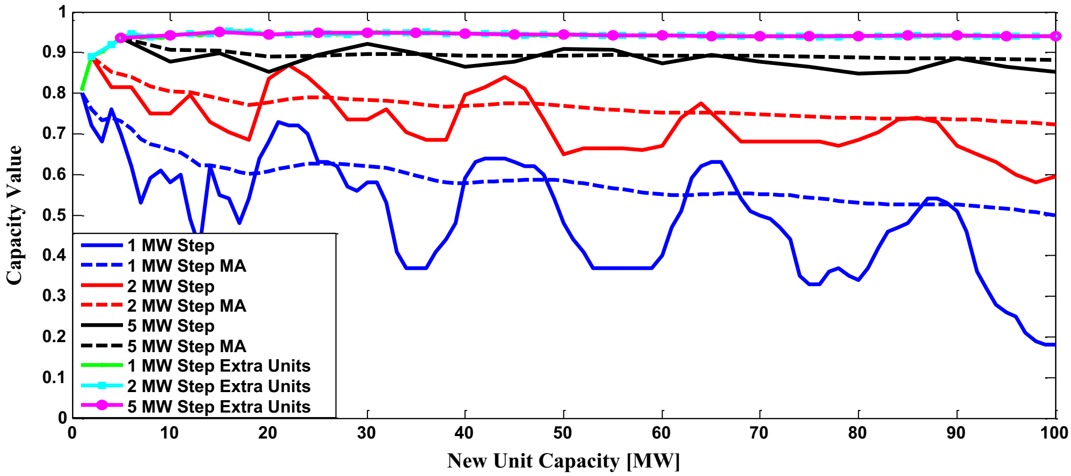

Figure 11. Comparing the charts of Section 3.1.2, 3.3.2, and 5.2.

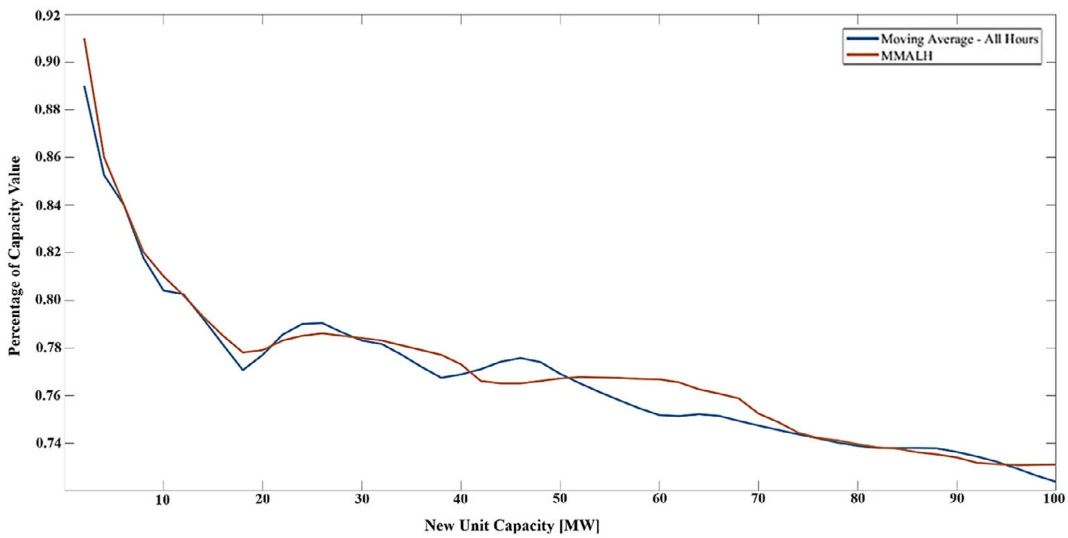

Figure 12. Comparing the results of moving average capacity considering all hours and limited hours.

inaccuracies and inconsistent capacity value evolution further hinder the effectiveness of these methods.

The article proposes a new metric called the MMALHs ELCC-based capacity value to overcome these limitations. This metric reduces the reliance on extensive data while providing a more accurate representation of capacity value behavior. Real-world case studies conducted in Belgium, Texas, and California validate the effectiveness of this proposed metric. This research recommends maximizing the capacity utilization factor through optimized design, advanced tracking systems, improved maintenance practices, and effective grid integration to enhance the performance of solar plants. Continuous monitoring and analysis of the utilization factor are essential for identifying areas for improvement and increasing overall productivity. By addressing the limitations of existing methods and introducing the MMALH approach, this research contributes to a better understanding and assessment of capacity value in PV power systems.

Potential future works can be aligned with the following recommendations 1) Expansion planning: in expansion planning, it is recommended to focus on robust modeling and analysis to accurately determine the capacity value of energy sources. Additionally, integrating renewable energy sources, designing appropriate market mechanisms, promoting technological innovation, and establishing supportive policies are essential for maximizing capacity value and ensuring a reliable electricity system. 2) Quantum computing integration: quantum computing holds immense potential for revolutionizing various fields, including energy and renewable technologies. In the context of PV farms, integrating quantum computing can offer significant advancements in capacity estimation, optimization, and simulation. Future research should explore the application of quantum algorithms and machine-learning techniques to enhance capacity value estimation, optimize PV farm layouts, and improve overall system efficiency.

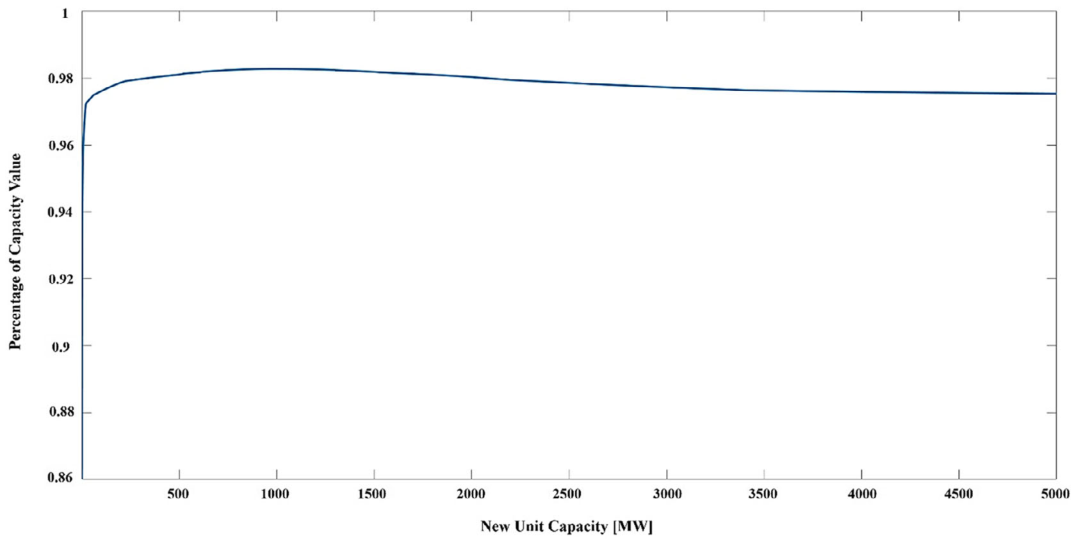

Figure 13. Changes in the value of each MW of capacity using MMALH-CV as the new unit capacity increases with variable steps.

Nomenclature

T	Study time interval [h]
$\overline{T}$	Limited-hours time interval [h]
G_t	Available conventional generation capacity at time t [MW]
$\overline{G}$	Installed nominal conventional generation capacity [MW]
V_t	PV unit production at time t [MW]
μ_{PV}	Average hourly PV production [MW]
σ_{PV}	The standard deviation of hourly PV production [MW]
ε	Loss of load expectation (LOLE) value of the system without PV [h year^{-1}]
ε^{PV}	LOLE value with the addition of PV [h year^{-1}]
$\overline{V}$	The nominal capacity of PV unit [MW]
L_t	Load level at time t [MW]
μ_S	Average St [MW]
σ_S	The standard deviation of St [MW]
B_t	The nominal capacity of the benchmark unit at time t [MW]
p_t	Probability of load loss at time t
ε^{ELCC}	LOLE value with the addition of PV and load [h year^{-1}]
ε^{B}	LOLE value with the addition of the benchmark unit [h year^{-1}]

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Keywords

adequacies, capacity outage probability tables, capacity values, loss of load probabilities, marginal values, reliabilities, sun-tracking systems

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