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Published in:
IEEE Access

DOI:
10.1109/ACCESS.2025.3620880

Published: 01/01/2025

Document Version
Publisher's PDF, also known as Version of record

IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 15 September 2025, accepted 5 October 2025, date of publication 13 October 2025, date of current version 21 October 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3620880

RESEARCH ARTICLE

Analysis of Capacity Credit of Wind Power and the Influence of Hydrogen Energy Storage

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This work was supported by the Academy of Finland as part of the Profi7 Project. The work of Ilkka Jokinen was additionally supported by the Walter Ahlström foundation.

ABSTRACT With an increasing share of wind power generation, it is crucial to analyze its availability and effect on the reliability of power systems, to maintain a high level of security of supply. Moreover, since the annual generation can vary greatly, long term analysis is required. Thus, this study examined two independent methods for determining the capacity credit of wind power, considering a long period of 18 years. The first method was a time-period-based capacity credit which only considered wind power generation, and the second one a risk-based method, which analyzed the complete power system and its level of reliability. Moreover, with the risk-based method, the analysis considered different installed capacities for wind power and possible hydrogen storage coupled to the wind power. The results from the time-period-based capacity credit determined, that 8.8% and 3.1% of wind power capacity can be expected the be available with 90% and 98% confidence levels, respectively. In addition, with the risk-based method, the ratio between additional load that a system can supply by including wind power and installed wind capacity, decreased from 14.5% to 4.3% when the wind capacity was increased from 5.68 GW to 30 GW. Moreover, coupling an energy storage to the wind power generation improved its utilization and simultaneously the capacity credit by 2.6-4.6 percentage points. Furthermore, to obtain these results, wind power generation was modeled from 2004 to 2021.

INDEX TERMS Capacity credit, effective load carrying capability, wind power, hydrogen storage, power system reliability.

I. INTRODUCTION

In the pursuit of reducing greenhouse gas emissions of their electricity generation, nations are promoting the increase of renewable generation technologies. Moreover, especially solar photovoltaic (PV) and onshore wind power are one of the cheapest generation technologies in most markets [1]. The International Energy Agency predicts that the yearly installed wind power capacity will increase from 108 GW to 167 GW globally by 2028 [2]. Nationally these increases can be even greater; for example, in Finland the wind power capacity is predicted to increase, by the national transmission system operator (TSO) [3], to 18-23 GW by 2030, in a power system with a historical peak load of 15.1 GW, whereas in 2022 it was 5677 MW.

As the availability of wind power is determined by the availability of wind, its generation is undispatchable by nature. Thus, when the share of wind generation increases, it is crucial to assess its impact on the power system, to guarantee a high level of security of power supply also in the future.

One widely used method for analyzing this reliability of generation, is capacity credit (CC). Several studies have utilized it as a metric in their analysis, although the definitions for it vary. However, these definitions of the capacity credit can be divided into two categories. The first one is a statistical, time-period-based approach, which examines how large share of the generation is available a certain amount of time. Thus, giving a minimum power generation capacity from a

The associate editor coordinating the review of this manuscript and approving it for publication was Xiaodong Liang.

power source, which can be expected to be available at any given moment with a certain level of confidence.

This method of the time-period-based capacity credit of wind power has been, and still is, widely used by TSOs in several countries, due to its low computational complexity and use of real historical data [4]. In addition, it has been examined in several studies. In [5], this method was used to evaluate the capacity credit between years from 2005 to 2008, using hourly wind power data from Nordel, a previous umbrella organization for the TSOs in the Nordic countries. It evaluated the capacity credit with the 90% confidence value, considering several time frames: high-load periods, seasonal periods, and whole years. They obtained values for capacity credit between January and February, a high load period, which were between 3% and 11%. Moreover, this methodology has been utilized by several TSOs; the Californian independent system operator analyzed a three year period, and found the capacity credit of wind to be between 15 and 30% during peak load months [6], the Southwest power pool applied this to a monthly analysis and found a capacity credit around 10%, whereas the New York system operator calculated capacity credits for summer and winter, which were 17% and 30% respectively [4].

The second type of methodology to analyze the capacity credit of wind is a risk-based approach, where wind power's impact on the Loss of Load Probability (LOLP) is studied. The capacity credit is then defined as the additional load that a power system can supply, once wind power is added to the system, while maintaining the same level of reliability. This approach estimates the Effective Load-Carrying Capability (ELCC) of a resource, by studying its effect on the power system as a whole [7]. Several studies have utilized this methodology, or a similar probabilistic one based on a different metric, to examine the capacity credit of wind power. Study [8] compared different interpretations of this method and concluded that the capacity credit was affected by the power system LOLE, higher CC with higher LOLE, and found that higher capacity credit was achieved with lower installed wind capacity. Likewise [9] concluded that the CC decreased with increased installed wind power capacity. In addition, this methodology has been used in [10], where the CC of wind was between 19.2% and 0.5% depending on the installed capacity, whereas in [11] an analysis consisting of two wind parks found the CC of wind power to be between 32.4% and 19.5% with a wind penetration level from 2% to 20%. Large variation in CC was found in [12] too, which utilized data from seven years, where the average CC of onshore and offshore wind power were 16% and 41%, respectively. A very high CC for wind, 66.7-68.5%, was presented in [13] for low installed capacity in a low reliability power system. In [14], the capacity credit of independent wind farms was found greater compared to dependent wind farms, and in [15] that the CC of multiple wind farms greater than individual ones. In [16] and [17] hybrid renewable systems and their capacity credits were examined, where [16] found standalone systems to have a higher CC compared to grid connected systems, and [17] that demand response improved the CC.

In addition to the time period based method, [5] also estimated the risk-based capacity credit for Finland, considering a 2000 MW wind power capacity. Three scenarios were analyzed, considering the wind power capacity in other Nordic countries, the availability of wind power in Finland, and generation capacity of wind power. By the analysis the risk-based CC was found to be between 5% and 20%, whereas the time-period-based CC was found to be between 3% and 11%. In addition, both methods were compared in [18], which concluded that chronological methods are more useful for system operators and probabilistic one for planning.

Furthermore, with the risk-based method there are studies which have considered the combined capacity credit of wind power and energy storage. For example, [19] found out that coupling storage operations to wind power could increase the capacity credit, whereas [20] found out that with storage the capacity credit increased, and that the increasement was greater with lower wind generation capacity. Moreover, in [21] the combined capacity credit of wind, solar, and energy storage was found to be greater than their individual ones.

In summary, the capacity credit of wind power has been studied by the time-period based method in [4], [5], and [6] and with a risk-based method in [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], including [12] with data from seven years. Moreover, studies [5], with four-year data, and [18] compared the two methodologies, and studies [19], [20], [21] examined the combined CC of wind power and a storage. However, to the authors' knowledge, there are no studies in current literature, which have analyzed the capacity credit of wind power with a long time frame, while considering the two different estimation approaches for the CC. This is crucial to consider, as wind power generation can have significant interannual variation in its generation, affecting the CC, as later presented in the Results. Thus, the novelty of this study is examining the capacity credit of wind power for a period of 18 years, with two methodologies, to provide robust results on the availability of wind power and its effect on the power system's reliability. In addition, this study analyses the annual variation of the capacity credit of wind powers, highlighting the necessity for research studying a long time frame. Moreover, the effect of coupling an energy storage to the wind power generation, and analyzing their combined capacity credit is examined, considering the same 18-year period, which furthers the knowledge in current literature.

The rest of this study is formulated as follows. Section II presents the materials and methods used to determine the time-period-based and risk-based capacity credit evaluations, as well as the storage analysis. Then, Section III will present the results, and Section IV concludes the paper and discusses the results.

II. MATERIALS AND METHODS

A. WIND POWER MODEL

Electricity demand has been stagnant for the last twenty years in Finland [22]. This means that a risk-based capacity credit evaluation can be performed considering a static wind power capacity through the years without losing temporal consistency. Thus, this study focuses on the period from 2004 to 2021.

To model the wind power generation, it is first necessary to acquire the hourly wind speed data for locations that hold significance from a wind power generation perspective. The most relevant locations for wind power production are along Finland's west and south coast, where winds are usually stronger and steadier [23], and where most of the existing wind power plants have been constructed. Hence, seven coastal locations, to represent the wind generation close to the largest wind farms in Finland, were chosen for the wind speed measurements. From north to south, they were:

- Simo (65°42'00"N 25°00'00"E)
- Kalajoki (64°18'00"N 24°12'00"E)
- Kannus (64°00'00"N 24°00'00"E)
- Vaasa (63°00'00"N 22°00'00"E)
- Närpiö (62°36'00"N 21°18'00"E)
- Isojoki (62°10'00"N 21°41'00"E)
- Pori (61°33'00"N 21°33'00"E)

Moreover, an accurate model can only be constructed if the wind speed datasets used are indicative of wind trends at blade height. Most direct measurements of wind speed are taken at around 10 meters above the ground, where the interferences with the ground and nearby objects are large, which results in inaccuracies when deriving the wind speeds for typical wind turbine heights. Instead, Reanalysis datasets, based on satellite observations and modelling data, were utilized as they are generally more accurate compared to extrapolation models [24], [25]. Several global reanalysis and high-resolution models are available online. This article used the Modern-Era Retrospective Analysis for Research and Applications Version 2 (MERRA-2) [26] by NASA, one of the most used in the industry.

From the Finnish Wind Power Association, data of every installed wind turbine in Finland was available [27]. The average hub height of the installed wind turbines, weighted on their rated power, is 135 meters. The closest available datasets provided hourly northward and eastward wind values at 100 meters above the ground, from which it was possible to derive the wind velocity (V_W) as:

$$V_W = \sqrt{V_E^2 + V_N^2} \angle V_W = arctan\left(\frac{V_N}{V_E}\right) \tag{1}$$

Where (V_E) and (V_N) were the northward and eastward wind values. With the wind speed data, an error function that measured the difference between the modelled and real power was created:

$$error = AVG\left(\sqrt{\sum\nolimits_{i=1}^{7} \left(x_i P\left(V_i\right) - P_{22}\right)^2}\right) \tag{2}$$

Where (x_i) represented the weighting coefficient and (v_i) the wind speeds for the seven locations, whereas (P_{22}) was the historical wind power generation during 2022. Starting from equal weights $x_i = 1$, a derivative-free, nonlinear programming solver was used to minimize the mean squared error. The solver produced a vector of weighting coefficients.

B. MODEL ASSESSMENT

This subsection evaluates the accuracy of the model. In Fig. 1 the duration curves of the modeled and actual wind generations during 2022 are presented. There it can be seen that in the lower wind speed region, the modeled generation was almost equal to the actual generation, while there was minor error margin with higher wind speeds. In Fig. 2 and Fig. 3 the chronological output from the modeled and actual wind generations are presented for two selected periods. In Fig. 2, the model follows the actual generation well, whereas in Fig. 3 the model's trend is similar to the actual data, but with an underestimation of the generated power. This difference is due to the use of static weights in the model, which therefore did not consider seasonal variations in the wind speeds. However, the error was mainly confined to the summer period and thus, the effect on the risk-based capacity credit was minor. Moreover, this uncertainty affected the risk-based capacity credit more that the time-period-based, which was affected negligibly, as its value is based on the analysis of the share of low wind generation values of a selected period, which accuracy was high, as presented in Fig. 1.

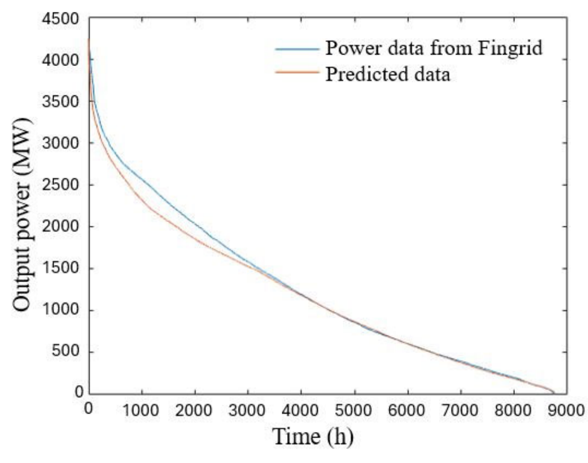

FIGURE 1. Duration curves for the modeled and real wind power generation during 2022.

C. APPLICATION OF THE MODEL TO THE PERIOD OF 2004-2021

Since the model, formulated based on the year 2022, produced a reliable result, the seven weights found with the derivative-free, nonlinear programming solver were used to derive the power that would have been generated in the period 2004-2021, if the 2022 wind turbine fleet had been used. The average correlation between the real and modelled wind generation was 91.2%, and the average RMSE 5.9%.

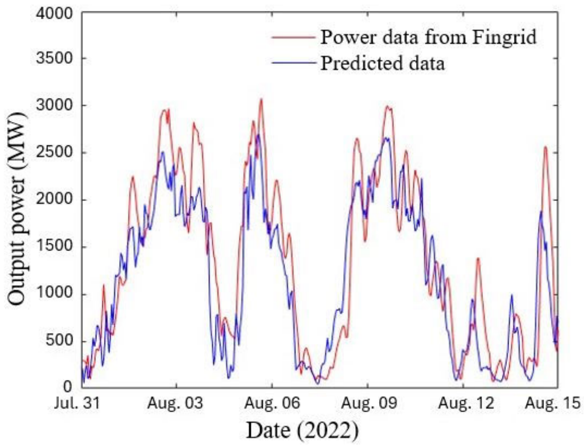

FIGURE 2. Good correlation between predicted and real wind generation data. For readability 400 hours were included.

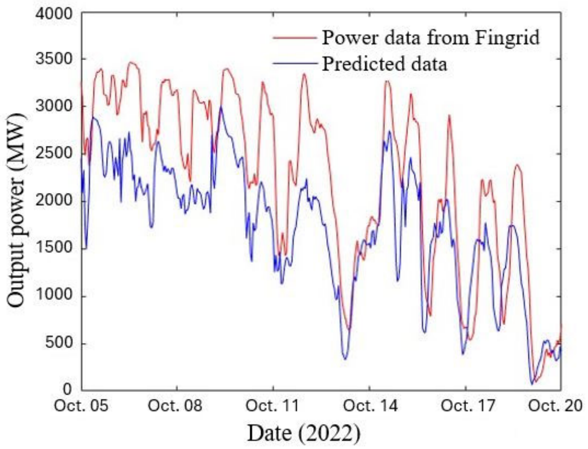

FIGURE 3. Underestimations of wind speed and thus wind power generation between predicted and real data, similar to [28]. For readability 400 hours were included.

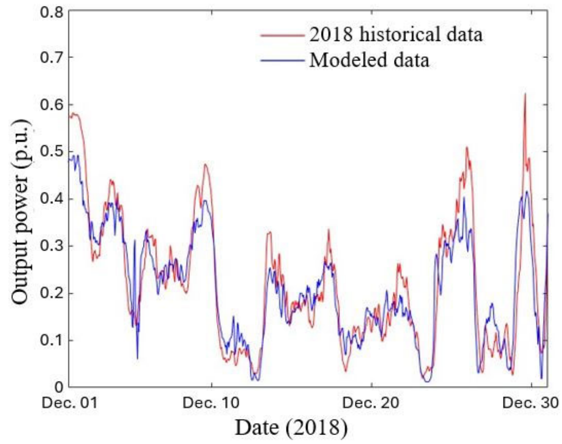

FIGURE 4. Real and modeled wind power output in December 2018.

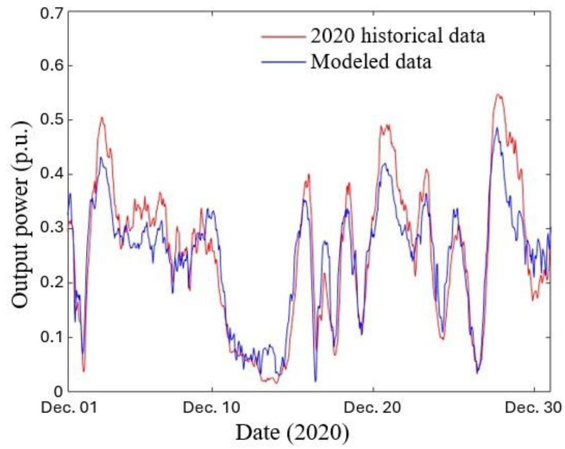

FIGURE 5. Real and modeled wind power output in December 2020.

In addition, in Fig. 4 and Fig. 5 selected months from years (2020 and 2018) are presented, where this good accuracy of the modeled generation compared to the historical generation is visualized. Note, that in the data presented in Fig. 4 and Fig. 5, the generation capacity was adjusted to correspond to the installed capacity of the respective year.

With the modeled wind power generation, the time-period-based capacity credit could be evaluated for the years from 2004 to 2021. The calculation method used to derive the capacity credit in this chapter consists of finding the wind power output that is exceeded 90%, 95%, 98% and 99% of the time, and dividing it by the total installed wind capacity [5].

In this analysis, different capacity credit values were calculated. Firstly, the capacity credit for the whole 18-year period was calculated, in order to give a single summarizing value for reference. To obtain it, the duration curve of wind power generation over the total 18-year interval was created. Then, the elements corresponding to 90%, 95%, 98% and 99% of the total time were found, and divided by the installed capacity at the end of 2022, which was 5677 MW, as also the generation was modeled to correspond to this capacity. Secondly, the capacity credit for winter periods was determined, as they are the most interesting periods to investigate, to assess generation adequacy. The winter period was considered to be each year from 1st of December to 28th of February. In addition, as both the two previous calculations considered the average capacity credit over the 18-year period, from 2004 to 2021, the capacity credit for each year was also calculated, to observe its annual variation. Finally, the top load hours were considered, namely the top 24 (day), 168 (week), 720 (month) and 1000 hours for every year, of which the average was computed.

D. EFFECTIVE LOAD-CARRYING CAPABILITY EVALUATION

This subsection will present the methods implemented to calculate loss of load probability, LOLP, loss of load expected, LOLE, and finally Effective load-carrying capability, ELCC. These metrics were utilized to determine the risk-based capacity credit of wind power.

In addition, data of the power plants operating in the power system were required. The Finnish Energy Authority [29] provides a list of every power plant in operation in Finland, which were used to construct the available generation capacity. For each power plant category, the summed rated capacities, forced outage rates (FORs), and average duration when unavailable [30] are presented in Table 1. In addition, in Table 1 the same parameters are presented for the available interconnection lines to neighboring countries.

TABLE 1. Total generation capacity and the forced outage rates, FORs, by generation technology and interconnection lines in Finland [29], [30].

Generation or interconnection	Installed capacity (MW)	FOR (%)	AVG duration of unavailability
Hydro power	2541	7.5	1 day
Nuclear power	4394	2	7 days
CHP biomass	1833	7.5	1 day
CHP coal	1557	10	1 day
Gas turbine	1780	5	1 day
SE1-FI	1200	0.05	7 days
SE3-FI	1500	3	7 days
EE-FI	1000	3	7 days
NO-FI	100	3.5	7 days

Unlike fossil-fueled and nuclear power plants, hydropower plants must consider the availability of their primary source, reservoir limitations, and the requirements for water flow downstream from the plants. In Finland 45% of the hydropower is run-of-river (ROR) hydro, which must be operated directly according to the water inflow [31]. Thus, 45% of the water inflow to hydropower plants was utilized for ROR hydropower and 55% to flexible hydropower connected to reservoirs. For the total inflow, a median value from 1978 to 2014 was utilized, with an annual energy of 11.3 TWh [32]. Moreover, for mitigating the computational burden related to the available capacity from hydropower, the water inflow to ROR hydro, and consequently the ROR generation, was modeled with three states in this study, namely 405, 1350 and 2100 MW, as presented in Fig. 6. Furthermore, for the same periods, the maximum capacity of hydropower was based on historical generation data between years 2010 and 2021, as 2541, 2445, and 2502 MW [33]. The flexible capacity of hydro power was thus the difference between the total and ROR capacity. In addition, for each hour the flexible hydropower was operated either at its maximum capacity or zero. This is visualized in Fig. 6, where the water inflow to ROR and flexible hydro, modeled water inflow and modeled ROR generation, and total hydropower capacity are presented for a year.

The operation of the flexible hydropower was adapted from [34], and optimized as in Eq. 3-9.

$$Min \sum_{t=1}^{T} P_t^{deficit} + \left(\sum_{t=1}^{T} \frac{P_t^{excess}}{P_t^{demand}}\right) \varepsilon \tag{3}$$

s.t

$$P_t^{demand} = P_t^{fixed} + P_t^{hydroflex} + P_t^{deficit} - P_t^{excess} \tag{4}$$

$$P_t^{hydroflex} = P_t^{hydroflexcapacity} \cdot b_t \tag{5}$$

$$SoC_t^{hydro} = SoC_t^{hydrostart}, t = 1 \tag{6}$$

$$SoC_t^{hydro} = SoC_{t-1}^{hydro} + Inflow_t^{hydroflex} - P_t^{hydroflex}, t > 1 \tag{7}$$

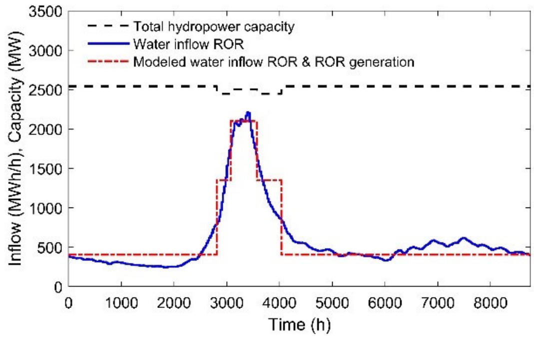

FIGURE 6. The median water inflow to ROR hydropower, modeled water inflow to ROR hydro, and total hydro power capacity [31], [32], [33], [34].

$$0.05 \cdot SoC^{hydromax} \leq SoC_t^{hydro} \leq SoC^{hydromax} \tag{8}$$

$$0.99 \cdot SoC^{hydromax} \leq SoC_t^{hydro} \leq 1.01 \cdot SoC^{hydromax}, t = T \tag{9}$$

where in the objective function the first term minimized the power deficit, ($P_t^{deficit}$), after all other available generators, and the second term allocated the possible excess generation from flexible hydropower to high demand hours. In addition, (P_t^{fixed}) in Eq. 4 represented the thermal and ROR hydropower generation capacity, as well as wind power generation when it was included. Eq. 5 used a binary variable b_t to limit the flexible hydro power, ($P_t^{hydroflex}$), to either its maximum or zero. In Eq. 6 to 9 the hydropower reservoir, (SoC_t^{hydro}), utilization was constrained between its minimum and maximum, and the final reservoir level to within 1% of its starting value.

With the power plant capacities and forced outage rates, a discrete numerical convolution process could be utilized, which was adapted from [35]. By this process, a capacity outage probability table (COPT) was possible to be formulated, which determines the probabilities to each generation outage state, i.e., defines the probabilities that a certain capacity in MW is on outage in a power system. Similar to [35], and assuming an already initialized COPT, let

- P(X) = Cumulative probability of X MW or more on outage for the existing table;
- P'(X) = Cumulative probability of X MW or more on outage for the new table;
- q = Forced outage rate of the new power plant;
- p = Availability of the new power plant (1-q);
- C = Capacity of the new power plant.

Then, the cumulative probability of having X MW or more on outage after the addition of a new power plant with capacity C is [35]:

$$P' = p \cdot P(X) + q \cdot P(X - C) \tag{10}$$

The formula was initialized considering that there are always at least 0 MW on outage [35]:

$$P(0) = P(< 0) = 1 \tag{11}$$

For every other MW value, the outage probability was initialized to 0 and then units are convolved using Eq. 10

recursively, with a 1 MW step size. Moreover, each power plant unit was assumed to operate by two-states.

This method yields to a Capacity Outage Probability Table, which defines the probability of X MW or more on outage at any given time. To compute the loss of load probability, LOLP, for a given hour i, it is sufficient to find the value corresponding to $(G_i - D_i)$ MW, where G_i and D_i are total generation and demand, respectively. Once the LOLP is computed for every hour, the loss of load expected, LOLE, is defined as the sum of LOLP for each time instant.

The effective load-carrying capacity, ELCC, of wind power generation was found by carrying out these calculations twice: first, by considering every power plant, except wind power, and secondly considering all power generation plants, including wind power as the generation time-series formulated in the previous Section. The inclusion of the wind power plants in the second calculation made the power system more reliable, by reducing the total Loss of Load Expectation for the period under analysis. The ELCC was computed by increasing the hourly load until the LOLE of the power system with wind power equaled the LOLE of the power system without wind power. The additional load that achieved this, was the Effective Load Carrying Capability. Moreover, often it is defined in relative terms, as was in this study, dividing the additional load by the installed capacity of the wind power plants.

Three reliability levels were studied with this method: two cases with either maximum or zero interconnection capacity, respectively. In addition, a realistic case was included where the reliability of the system, defined with the LOLE, was 2.1 hours per year, by limiting the interconnection capacity, in accordance with the government target [36].

E. FUTURE POWER SYSTEM

In the previous subsection, the capacity credit was defined considering the power generation as it was at the end of 2022. However, in the future it is likely that the generation capacity of wind power is increased to even greater levels, and its share of the power generation is increased. Moreover, this increase could influence the reliability of the power system. Thus, the capacity credit of wind power generation with increased generation capacities was further examined here. Furthermore, to mitigate the challenges related to the intermittent nature of wind generation and improve generation supply reliability, an energy storage was additionally included in the analysis, in combination with wind power.

Here the analysis considered a power system which, without wind power generation and storage, had a LOLE of 2.1 h/year, representing a realistic system reliability. The power system included the generation capacities as presented in Table 1. However, the interconnection capacity was reduced to 63.5%, 2412 MW, of the rated capacity, to obtain this realistic system reliability. The future considerations aimed then to match this reliability with the added wind generation, storage and load. The capacity credit was defined and calculated similarly as in the previous Section II-D, and considered the load and wind power generation from 2004 to 2021, as previously.

Firstly, only the capacity of installed wind power generation was increased. The selected increased capacity levels were: 5677 MW (2022 capacity), 7000 MW (roughly the 2023 capacity), 10000 MW, 15000 MW, 20000 MW, 30000 MW. The new generation profiles were obtained by scaling the modeled wind power generation in Section II-C, with a corresponding linear scaling factor. As the capacity was increased the additional load, which was possible to be supplied, maintaining the same LOLE of 2.1 h/year, and the corresponding capacity credit were calculated for every increase of wind power capacity, as in Section II-D.

Secondly, energy storage was considered, as a hydrogen storage with a round-trip efficiency of 50% (from power to power) [37], [38]. The energy capacity of the storage was defined such that a larger storage would not have provided any additional benefits, and such the operation was not limited by the storage capacity. That is, the energy capacity of the storage was just enough to supply the required energy without depleting the storage. The energy storage was coupled to the wind power generation and was operated by a heuristic algorithm, which functioned as follows; when the load at a time instant was lower than the mean load, the excess wind generation could be utilized to charge the storage, whereas with load greater than the mean load the energy storage could supply power to the grid. Thus, the energy storage aimed to lower the difference between the load and wind power generation, to increase the utilization of wind power and hence improve the capacity credit.

Moreover, as the resulting energy capacity requirements for the energy storage were rather high, two cases with limited energy storage capacities were also examined. In them, the energy capacity of the storage was limited to 67% and 33% of the capacities in the unrestricted case, for each increasement of wind power generation. Thus, the additional load was then recalculated to bring the LOLE of the power system to 2.1 h/year, and the capacity credit was determined.

III. RESULTS

This Section present the results of the capacity credit of wind power calculated with the time-period-based method and the risk-based method. Moreover, for the risk-based method a combined capacity credit of wind power coupled to a hydrogen energy storage is presented.

A. TIME-PERIOD-BASED CAPACITY CREDIT

The time-period-based capacity credit considered solely the wind power generation, and thus, the analysis was neither affected by the rest of the power system, nor the load. With this method, the capacity credit determined the share of generation capacity which was available a certain share of time. Several time-horizons were analyzed, to determine the capacity credit in different situations. In addition, the time-period-based capacity credit was analyzed during high load periods. First, the capacity credits for wind power for the total 18-year period was found, considering the confidence levels of 90%, 95%, 98%, and 99%, which are presented in Table 2. This is a summary value for the total period, and thus represents an average during the18 years.

TABLE 2. Time-period-based capacity credit for the total 18-year period from 2004 to 2021.

	CC (90%)	CC (95%)	CC (98%)	CC (99%)
Capacity credit	8.8%	5.5%	3.1%	2.0%

As presented in Table 2, the capacity credit of wind power during the total 18-year period, with the selected confidence levels, was between 8.8% and 2%, meaning that 90% of time, the wind power generation was greater than 8.8% of its installed capacity, and 1% of the time the generation was at most 2.0% of its installed capacity.

In addition, the capacity credit of wind power was examined for each year between 2004 and 2021, which are presented in Table 3, to observe the yearly variations. Apart from an unusually windy 2020, the annual variation from the average, was always within ±20%. The average values are slightly different compared to the analysis for the complete period in Table 2, since they were calculated as the mean of the capacity credit for every year, instead of values for the whole period.

TABLE 3. Time-period-based capacity credit values for each year from 2004 to 2021. In each column, the highest and lowest values are highlighted.

Year	CC (90%)	CC (95%)	CC (98%)	CC (99%)
2004	8.0%	5.0%	3.0%	2.0%
2005	9.7%	5.8%	3.1%	2.0%
2006	9.1%	5.7%	3.3%	2.1%
2007	9.1%	5.9%	3.4%	2.1%
2008	8.3%	5.1%	2.9%	1.9%
2009	7.5%	5.0%	2.8%	2.0%
2010	7.8%	5.3%	3.1%	2.0%
2011	7.9%	5.0%	2.7%	1.7%
2012	9.0%	5.5%	3.1%	2.0%
2013	10.5%	6.7%	3.2%	2.0%
2014	7.4%	4.7%	2.9%	1.9%
2015	10.7%	6.5%	3.7%	2.4%
2016	7.6%	4.6%	2.6%	1.6%
2017	8.9%	5.9%	3.4%	2.1%
2018	9.6%	5.5%	3.0%	1.9%
2019	9.3%	6.0%	3.1%	2.0%
2020	12.1%	7.4%	4.1%	2.3%
2021	8.5%	5.5%	2.8%	1.8%
Mean	8.9%	5.6%	3.1%	2.0%

Moreover, the same procedure was then carried out for each winter, from December 1st to 28th of February, as it represents the most critical period for the power system, as then the load is the highest. The capacity credit values during these periods are presented in Table 4, for the years from 2005 to 2021, as for 2004 the data for winter period was not complete.

There, two interesting notions were observed. Firstly, the average values were notably higher compared to the annual capacity credit values, especially the 95% and 98% ones, where the relative increase was close to 50%. The positive correlation between the high demand, and low ambient temperature, time-period and wind power generation can be attributed to the increased density of cold air and the smoother surface of snow-covered or frozen ground, permitting the buildup of stronger winds [39]. Secondly, considering the winter period, the annual variation from the average was greater, as for some years it exceeded ±50%. Partly this was affected by the inclusion of only three months for each year, as random variations carried more weight. Nonetheless, this showed that during some years wind production can be much lower during winter, and then the electricity system could be severely challenged, and further increasing the risk of load shedding and increased price of electricity.

TABLE 4. Time-period-based capacity credit for wind power, for each winter period between 2005 and 2021, from Dec. 1st to Feb. 28th. Values for 2004 were not presented, as only part of the period would have been included. In each column, the highest and lowest values are highlighted.

Year	CC (90%)	CC (95%)	CC (98%)	CC (99%)
2005	14.9%	10.6%	5.9%	4.1%
2006	8.0%	5.9%	3.3%	2.3%
2007	10.0%	7.9%	4.2%	2.6%
2008	18.7%	12.5%	6.1%	3.2%
2009	7.2%	5.1%	2.5%	1.8%
2010	10.5%	8.8%	4.5%	2.8%
2011	5.7%	4.8%	2.7%	1.8%
2012	13.8%	11.9%	6.2%	3.5%
2013	12.6%	11.2%	4.9%	2.5%
2014	14.0%	11.7%	5.6%	3.5%
2015	14.9%	11.1%	5.5%	3.5%
2016	10.9%	8.5%	3.8%	2.1%
2017	12.1%	10.4%	5.7%	4.1%
2018	7.4%	6.5%	4.0%	2.6%
2019	8.8%	6.9%	3.7%	2.6%
2020	17.8%	13.7%	6.4%	3.8%
2021	7.4%	6.7%	3.1%	2.1%
Mean	11.1%	8.8%	4.5%	2.8%

Lastly, an analysis of the top load hours was done, which considered the wind generation during the selected hours, based on the load during those hours. In other words, for example the 'Top 24 hours', reflects the individual 24 hours during which the load was the highest during the year. Then, the wind generation corresponding to these hours was considered for the analysis. The same consideration was repeated for 168, 720, and 1000 highest load hours, and the results are presented in Table 5. Moreover, the consecutive time period with the highest load was further analyzed for 24 and 168 hours, which are presented as 'Top day' and 'Top week' respectively, in Table 5. The values in Table 5, present the mean values during the years between 2004 and 2021.

B. RISK-BASED CAPACITY CREDIT

The risk-based capacity credit was analyzed as presented in Section II-C, and it determined how much additional load a

TABLE 5. Time-period-based, capacity credit values for top load hours. The analysis was carried out for every year, and the average is shown here.

Period	CC (90%)	CC (95%)	CC (98%)	CC (99%)
Top 24h	6.0%	3.8%	1.6%	1.0%
Top 168h	7.5%	5.1%	2.9%	1.5%
Top 720h	9.5%	6.1%	3.5%	2.3%
Top 1000h	10.0%	6.3%	3.6%	2.4%
Top day	9.1%	7.2%	5.2%	3.6%
Top week	7.2%	4.8%	2.7%	1.5%

power system can supply, when including wind power, while retaining the same level of reliability, which was measured as the loss of load probability, LOLE, of the system. Then, the value of the capacity credit was the additional load divided by the installed capacity of wind power. Thus, the risk-based capacity credit considers the complete power system, that is, the probability that the power plants are in operation and the varying system load. The examination was first conducted with the same wind capacity as in 2022, and then considering increased generation capacities for the future, and possible energy storage. All analyses considered the 18-year period.

1) EXISTING POWER SYSTEM

Considering the installed capacity of wind during 2022, 5677 MW, three cases were studied here: one where the rated interconnection capacity with neighboring countries was assumed to be available, one with no interconnection capacity, and one where the interconnection capacity was limited to 63.5% of the rated capacity, to 2412 MW, in order to reach a LOLE of 2.1 h/year, which represents a power system with a targeted reliability level.

The first analysis considered 3800 MW of interconnection with neighboring countries, limited only by the possibility of line faults, as in Table 1. With such a high generation and interconnection capacity, the LOLE in the Finnish power system, would be 0.37 hours per year, which is an extremely strong and reliable power system. Then, the capacity credit of wind power was 12.4%.

In the other extreme, where import capacity from abroad was null, the generation system would be in great difficulty. By this assumption, the LOLE rose to 19.5 hours per year, and thus wind power would contribute more to the system reliability, with a capacity credit of 15.8%. Lastly, considering the restricted interconnection capacity to 2412 MW, resulted in a power system with a LOLE of 2.1 hours per year. With this interconnection capacity the capacity credit of wind power became 14.5%.

These results are generally higher than the time-period-based ones. This indicates a positive correlation between wind power generation and load, as already seen for example in [40] and [41].

2) FUTURE POWER SYSTEM

As presented in Section II-E, here the value of the capacity credit of wind power was analyzed with increased capacity levels, to examine future power system scenarios. In addition, the coupling of an energy storage with wind power was analyzed and their combined capacity credit determined.

Here the power system was assumed to included 2412 MW of interconnection capacity to neighboring countries, which results in a LOLE of 2.1 h/year, without wind power and storage, with the historical load. As with previously, when the wind power generation, and later storage, was included, the load was increased to obtain a new power system with a LOLE value of 2.1 h/year, to match the same level of reliability. In Table 6, the impact of the generation capacity of wind power on its capacity credit is presented. There it can be noted that as the installed capacity of wind power increased, the capacity credit of it decreased.

TABLE 6. Wind power capacity credit and the related additional load by installed wind power capacity. In the Additional load column, the percentage value in brackets is with respect to the peak load (15.1 GW).

Wind capacity (GW)	Additional load (GW)	Capacity credit (%)	LOLE (h/year)
5.68	0.82 (5.5%)	14.5	2.1
7	0.93 (6.2%)	13.3	2.1
10	1.07 (7.1%)	10.7	2.1
15	1.17 (7.7%)	7.8	2.1
20	1.27 (8.4%)	6.3	2.1
30	1.30 (8.6%)	4.3	2.1

Moreover, the combined capacity credit of wind power and a hydrogen energy storage, which was coupled to the operation of wind power, as presented in Section II-E, was analyzed, which results are presented in Table 7. Then, the capacity credit was defined as the share between the additional load possible to be supplied by the power system and the summed capacity of wind power and storage output power. The output power of the storage was the amount the storage could supply power to the grid. Again, the reliability of the power system with and without wind and storage was 2.1 h/year. Comparing the capacity credits with the hydrogen storage coupled to wind power, it is clear that the storage was able to increase the availability of wind power generation, as the capacity credit increased, when compared to the respective amount of wind power, as in Table 6. However, the trend was the same as with only wind power; with increased amount of wind power generation capacity, the capacity credit decreased. Moreover, with increased amount of wind generation, the required capacity of the hydrogen storage is greatly decreased, as wind generation was significantly higher.

As presented in Table 7, when the capacity of the hydrogen storage was not limited, but assumed such large that an additional capacity would not have provided additional benefits, its size became rather large. Thus, two cases where the energy capacity of the hydrogen storage was limited to 67% and 33% of the unrestricted capacities presented in Table 7 were studied. The results, with these storage capacities, of the combined capacity credit of wind generation and hydrogen

TABLE 7. Capacity credit of wind power and unrestricted hydrogen storage capacity. The system LOLE was 2.1 h/year.

Wind capacity	Storage energy capacity	Storage output power	Additional load		Capacity credit
(GW)	(GW)	(GW)	(GW)		(%)
5.68	135	3.13	1.68	(11.1%)	19.1
7	110	2.97	1.72	(11.4%)	17.3
10	90	2.84	1.84	(12.1%)	14.3
15	65	2.68	1.91	(12.6%)	10.8
20	55	2.46	2.00	(13.3%)	8.9
30	40	2.22	2.34	(15.3%)	7.3

TABLE 8. Capacity credit of wind power and hydrogen storage with limited storage energy capacity. The system LOLE was 2.1 h/year.

Wind capacity	Storage energy capacity	Storage output power	Additional load		Capacity credit
(GW)	(GW)	(GW)	(GW)		(%)
Storage capacity 67% compared to Table VII					
5.68	90	3.03	1.55	(10.2%)	17.8
7	74	2.93	1.63	(10.7%)	16.4
10	60	2.80	1.74	(11.5%)	13.6
15	44	2.63	1.82	(12.1%)	10.3
20	37	2.44	1.93	(12.8%)	8.6
30	27	2.19	2.19	(14.5%)	6.8
Storage capacity 33% compared to Table VII					
5.68	45	3.00	1.40	(9.3%)	16.1
7	36	2.90	1.48	(9.8%)	15.0
10	30	2.78	1.61	(10.6%)	12.6
15	21	2.64	1.67	(11.0%)	9.5
20	18	2.43	1.81	(11.9%)	8.1
30	13	2.18	2.01	(13.3%)	6.3

storage by installed wind capacity are presented in Table 8. As previously, the LOLE of the power system was 2.1 hour per year.

With the limited energy capacities of the hydrogen storage, the combined capacity credit of wind power and the hydrogen storage decreased, compared to values with the unrestricted storage in Table 7. However, these decreases were not huge, and as they were achieved with notably smaller storage sizes, limiting the storage could be beneficial.

Moreover, on a general level, when interpreting the results for the risk-based capacity credit, it can be noted that the additional load that the power system can adopt when adding wind power was relatively small compared to the installed capacity of wind power. Furthermore, as the installed capacity of wind power increased, the share of additional load that could be added decreased, as noted with the decreased capacity credit. Including an energy storage coupled to the wind power increased the capacity credit, i.e., the share of the additional load that could be added to the system, compared to the installed capacity of wind power and energy storage output capacity. Moreover, it is good to note that with the storage included, also the generation capacity increased as the output power capacity of the energy storage was able to supply power. However, the combined capacity credit of wind and storage considered this, and the capacity credit increased compared to not including a storage.

IV. CONCLUSION AND DISCUSSION

In this study the capacity credit of wind power was examined by two methodologies, the time-period-based and the risk-based ones, considering data from 18 years from Finland. Moreover, the effect of hydrogen energy storage coupled to the wind power was analyzed.

With the time-period-based methodology, which only considered the wind power generation, the capacity credit of wind power was 8.8% with a confidence level of 90% and 2% with a confidence level of 99%. That is, 90% of time the wind generation was greater than 8.8% of the installed capacity. In addition, the capacity credit was analyzed for all years separately, during the 18-year period, which presented that the annual difference in the CC was at most 64% from year to year, although between most years the variation was lower. Nevertheless, this highlights the importance of considering a long period for the analysis. Moreover, it was found that the capacity credit was higher for winter period, i.e., the high load period, compared to the complete years. This indicated that there is a negative correlation between the wind generation and ambient temperature.

For determining the risk-based capacity credit, the complete power system was considered, including different power plants and their forced outage rates, the power system load, and the wind generation output. Then the capacity credit was defined as the ratio between the additional load that the system could supply and installed wind capacity, by adding wind power generation, while maintaining the same level of reliability as without the wind power and additional load, measured by the LOLE. It was found that with the generation capacity in 2022, 5.68 GW, the capacity credit of wind power was 14.5 %, with a system LOLE of 2.1 h/year. And when the wind capacity was increased to 30 GW, the CC decreased to 4.3%. This trend was similar as found in the previous studies presented in Section I. Moreover, the combined capacity credit of a hydrogen energy storage coupled to the wind power generation was also modeled. It was found that including the storage improved the capacity credit, and with a larger storage size the improvement was greater. However, even with a reasonable storage size of 45 GWh, and 5.68 GW of wind, the capacity credit increased from 14.5% to 16.1% when including the storage.

Comparing the two methodologies, it can be noted that their capacity credit values were somewhat different. However, as they were defined differently, this was anticipated. Thus, instead of comparing them, they should be interpreted to describe their results as they were defined; the time-period-based as the share of generation capacity from wind power that can be expected to be available a certain amount of time, and the risk-based one as the additional load that can be supplied by the power system when including the wind power generation. In addition, the risk-based CC decreased as the installed wind capacity increased and approached the values obtained for the time-period-based capacity credit.

This study utilized modeled wind generation data based on wind speed data from the Reanalysis dataset MERRA-2 as presented in Section II-A. Although the generation was verified to correspond well to the historical generation, presented in Section II-B, including experimental measurement data would provide further knowledge on the capacity credit. In this study the scope was to obtain results from a long time period for which the modeled wind generation was best suited. However, the reader is directed to studies [5] and [21] for further reading on the capacity credit with measured wind generation data.

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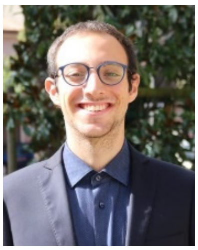

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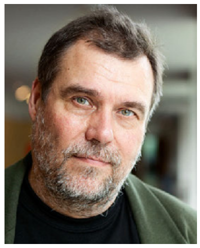

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