Calculation and Validation of Weather-Informed Renewable Generation in the US based on ERA5 Hourly Weather Measurements

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***Abstract*—Due to the benefits of direct inclusion of weather measurements in the power flow studies compared to using cumulative utility capacity factors, we introduce a methodology for the estimation of renewable energy output from detailed ERA5 data based on the U.S. Energy Information Administration generator data and power models and then validate the calculated results of each generator, using publicly available resources. Validation is performed by comparing our estimations against publicly available data for the largest renewable generators in the U.S. The analysis reveals strong correlations with reference capacity factors, underscoring the effectiveness of our approach. This validation not only supports the proposed strategy but also highlights its potential for improving renewable energy models.**

***Index Terms*—renewable generation, weather data resources, validation, power systems planning**

I. Introduction

Renewable energy, increasingly integral to power generation, stands out for its environmental sustainability and cost efficiency. In 2022, approximately 17% of the U.S. power generation capacity originated from renewable sources, a figure anticipated to escalate as wind and solar projects expand [1], [2]. The report [3] by the Energy Systems Integration Group underscores the critical need for detailed weather datasets to support power system planning and analysis amidst increasing reliance on renewable energy sources. The report highlights performance of wind and solar generators is profoundly influenced by weather conditions and with the growing dominance of renewable sources, it becomes crucial to model the impact of weather variations on the power grid over time, particularly for operational and planning studies. Incorporating a diverse array of potential weather scenarios directly into operational and planning frameworks offers significant advantages. This work leverages historical weather data to inform current power system analyses, recognizing that weather patterns in a given area may recur while the power grid evolves. Embracing a broader spectrum of weather scenarios enhances the grid's reliability and resilience by preparing for a wider range of contingencies.

The potential to accurately simulate various weather conditions offers a valuable tool for forecasting demand and power generation more precisely. This topic has earned considerable attention in the literature, with a significant focus on solar energy production (such as references [4], [5]) and wind energy (such as [6], [7], and [8]). Early research in this area in 1986, [9] initiated the study of weather's influence on the reliability of power system equipment and its failure rates, on top of the focus on the weather's impact on the load or generation. This area of research was further developed in a 1991 study [10], which highlighted the importance of integrating weather variables into power system assessments, especially in relation to the contingencies or outages during extreme weather events. More recent studies, such as [11], explore the significance of weather in evaluating the resilience of power system infrastructure. Reference [12] introduces "Renewables.ninja," model [13] tool designed to estimate the global output of weather-dependent renewable energy sources. The calculations are available for year 2019. Reference [14] introduces the PLUSWIND data repository, which offers hourly wind speeds and estimated generation data for nearly all U.S. wind plants from 2018 to 2021, facilitating the analysis of geographic and temporal variations in wind generation, despite the challenges of accessing and interpreting meteorological model estimates.

With the growing interest on incorporating weather data into the planning and operational strategies of power systems, previous work [15] suggested directly integrating weather measurements into power flow calculations. The researchers in [15] applied historical weather data from organizations like the International Civil Aviation Organization (ICAO) and the World Meteorological Organization (WMO) [16], [17]. However, these data sources often lack completeness and fail to cover all relevant meteorological parameters crucial for power systems, such as wind at both 10 meter and 100 meter elevations, "Total sky direct solar radiation at surface" or "direct horizontal irradiance", and "Surface Solar Radiation Downwards" or "global horizontal irradiance" which are required for calculating the power outputs of wind turbies and solar cells. Consequently, this paper is presenting the use of ERA5 data, as recommended by [18], for modeling wind power generation. Despite its benefits, integrating detailed weather data like ERA5 into power grid operations and planning presents numerous challenges, including computational complexity and limited accessibility of weather data for direct inclusion in optimal power flow. For this, an approach for storing and loading weather data efficiently is presented in [19].

This paper presents calculating approximate MWh power outputs of renewable resources using ERA5 weather measure-

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ments, with a validation against available power generation of these resources. The initial objective is to analyze key weather data and conduct simulations to estimate the available hourly capacities and power outputs of renewable energy generators, based on their resource availability. Power curves of wind and solar installations, and renewable generator parameters such as turbine model, installed rated capacity, hub height, and power point tracking are derived from EIA–860 data [1]. These calculated weather-informed capacities or generation outputs, are then cross-referenced with the available resources from 2019 and 2021 for validation.

The paper is structured to first elaborate the data preparation and models used in the study (Section II), followed by the methodology for calculating weather-informed capacities of wind and solar generators (Section III). Section IV uses the available capacity factors of each renewable generator to validate the calculated hourly capacities over the year. Then, the paper concludes and mentions future research directions in this area at Section V.

II. Data Overview

A. Input Weather Data

ERA5 represents the latest advancement in weather data reanalysis, constituting the fifth generation of such analyses. It is a retrospective analysis of global climate and weather conditions, spanning detailed hourly weather measurements from 1940. This initiative, undertaken by the European Centre for Medium-Range Weather Forecasts (ECMWF), is encapsulated in the acronym "ERA," which stands for "ECMWF Re-Analysis" discloses hourly data of a wide range of atmospheric, terrestrial, and oceanic climatic elements. This is achieved by integrating extensive historical data with sophisticated modeling and data assimilation technics. The result is an exhaustive and nuanced portrayal of climatic and weather patterns over extended periods. ERA5's utility spans numerous fields, including climate study, weather prediction, and environmental modeling, due to its detailed and long-term coverage of weather and climate data [20].

This study incorporates a range of high-quality ERA5 weather measurements that have an impact on power systems, such as wind speed, wind direction at the surface and 100 meters, cloud coverage, temperature, dew point for humidity, diffuse and direct solar radiation gathered hourly from numerous weather stations at each 0.25-degree grid of latitudes and longitudes across the continental U.S. from 1940 to the current time. However, the data is not limited to the United States and can be downloaded for the whole world using the code from [21]. Reference [19] introduces a new and efficient data format to store and load the weather data on power systems for studies such as power flow in a way to use less memory than regular file formats like csv files and use the common power flow strategies without making them computationally infeasible.

B. Generator Data and Weather Models

The next step is to extract generators' data. The rated or installed capacities and locations of renewable generators in the U.S. is readily accessible from the annual EIA–860 datasets [1]. Reference [22] describes the development and application of power flow models using the EIA–860 dataset.

This paper uses the installed generators as of the end of 2022, which included 1,508 wind generators (totaling 142 GW) and 5,778 solar generators (totaling 72 GW). These datasets provide detailed information on each generator, including fuel type, capacity, precise geographical location, renewable model used, hub height of wind turbines and power point tracking model for tilt angle and azimuth angles of solar cells.

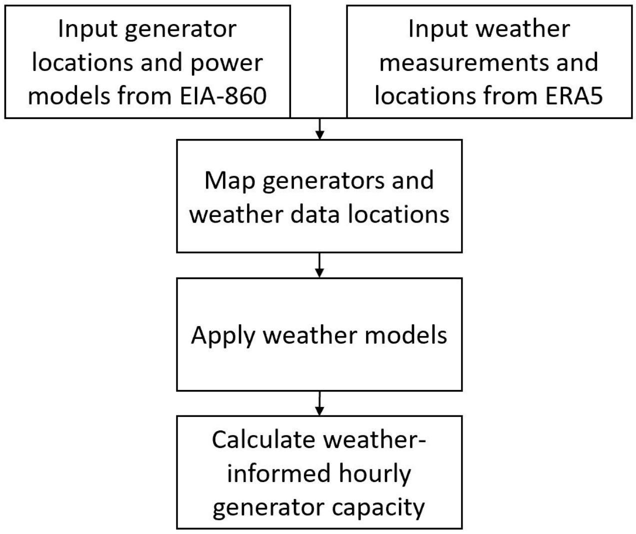

Fig. 1: Approach to calculate weather-informed wind and solar generator capacity with direct inclusion of ERA5 weather measurements.

As highlighted, a key advantage of the proposed strategy for directly incorporating weather measurements into operational and planning considerations is the ability to analyze a specific power grid across a vast array of historical and future weather scenarios. These scenarios might not align with the chronological development of the grid's infrastructure. Given the dynamic nature of the power grid, this approach is particularly valuable for assessing the impacts of extreme weather conditions; for instance, the effects of a severe weather event from 1940 can be examined within the context of today's grid. Recognizing that any weather event that occurred once in a region could potentially recur, examining a wide range of scenarios enhances our understanding and aids in the more effective planning of the grid's resilience.

III. Methodology

The overall strategy used in this paper to calculate the renewable generation capacities and power output generation is based on directly including weather data in power flow or optimal power flow (OPF) as shown in Figure 1. The process starts by using ERA5 hourly weather data explained in the previous section, from January 1, 1940, to the current time. Then the weather data geographically aligns with the generators using their coordinates, ensuring accurate mapping of environmental conditions to each generator with the same strategy explained in [15]. After the weather measurements are mapped with the closest generator, data is applied to calculate the output power of wind turbines and solar plants based on their types and classes that are publicly available across the United States. However, this strategy is not limited to North America and can be applied to any other part of the world with available generator data.

TABLE I:
Validation of Wind Generation Calculation Methodology with 2021 Data

Capacity (MW)	Calculated (MWh)	MERRA2 (MWh)	HRRR (MWh)	Diff MERRA2 %	Diff HRRR %	Corr MERRA2	Corr HRRR
1027	3,730,169	3,779,031	3,992,740	1.3	6.6	0.85	0.88
999	3,290,534	3,824,998	3,793,358	14.0	13.3	0.89	0.91
600	1,449,334	1,394,060	1,671,831	-4.0	13.3	0.74	0.75
525	1,297,587	1,359,530	1,544,938	4.6	16.0	0.82	0.76
522	1,614,545	2,176,205	2,289,927	25.8	29.5	0.50	0.35
503.2	1,524,060	1,651,917	1,816,467	7.7	16.1	0.83	0.78
500.6	1,779,085	1,964,194	1,914,096	9.4	7.1	0.85	0.86
500	1,285,162	1,289,423	1,312,678	0.3	2.1	0.86	0.86
498.4	1,332,392	1,877,023	2,086,070	29.0	36.1	0.75	0.78
491.6	1,546,443	1,597,945	1,610,086	3.2	4.0	0.87	0.85

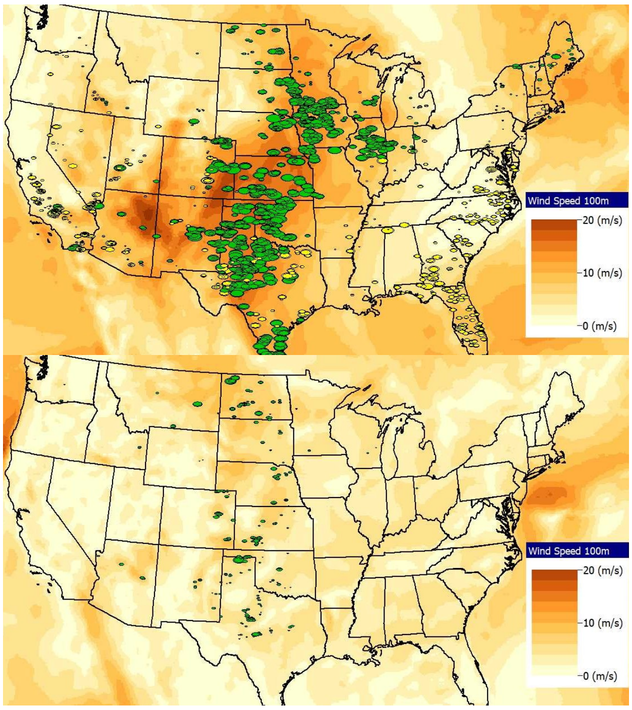

Fig. 2: High availability of wind and solar generation on April 22, 2022 (upper Figure), and Low availability of wind and solar generation on September 7, 2022 (lower Figure)

TABLE II:
Characteristics of the Studied Largest Wind Turbines in EIA–860 2022 Data

EIA Plant Code	Capacity (MW)	Hub Height (m)	Location
64665	1027	89	TX
63479	999	90	OK
60619	600	80	CO
63209	525	87	TX
63578	522	80	NM
62516	503.2	80	WY
64710	500.6	89	TX
65763	500	114	TX
62952	498.4	80	TX
62853	491.6	105	CO

This paper utilizes four generic wind models and one solar model from [15] to incorporate weather measurements like wind speed, wind direction, radiation and cloud coverage directly into the power system model. This approach allows for a more accurate calculation of wind and solar photovoltaic generation capacities under varying weather conditions. Weather data is mapped to renewable generators based on their geographic proximity, enabling the use of hourly weather measurements to calculate available weather-dependent generator capacities and power outputs. The models employ power curves from the EIA–860 data [1], which include specific generator model numbers. Wind turbines' capacities are calculated using a speed-power curve, while solar PV generation capacity is determined based on radiation, cloud coverage and PV factors such as the rated installed power, the type of solar PV tracking (fixed, single-axis, dual-axis), the used azimuth and tilt angles, and the assumed sky diffuse factor. These models are an outcome of integrating various sources, including [23]–[26], to provide a realistic representation of generator performance under different environmental conditions.

For a more precise PV output calculation, using the inverter loading ratio [27] is proposed. This ratio models the fact that the DC power output of a solar PV is often larger than the AC power due to system losses, conversion losses, power factor and inverter clipping [28], [29]. A high DC-AC ratio means the solar panel's DC capacity is significantly larger than the inverter's maximum AC output capacity. When the DC output from the solar panels exceeds the inverter's AC output capacity, the excess energy is not converted to AC. This is known as inverter clipping and is estimated in [30].

The simulation results of direct inclusion of weather measurement are visually represented in figures that display the spatial distribution of wind and solar generation. These figures use the Geographic Data View (GDV) approach, as outlined in [31], [32] and contour mapping technics [33] to increase the situational awareness of the grid status. The examples of these visualizations includes the hour in 2022 with the highest (Figure 2 upper) and lowest (Figure 2 lower) total wind and solar generation with contours of wind speed at 100 meters height. These Figures represent wind generation with green ovals and solar generation with yellow ovals, whose sizes are proportional to the MWh power outputs of these sources.

After the outputs or available capacities of renewable resources are calculated, publicly available resources are used to validate the results. For wind turbines' output power validation, reference [14] proposes a strategy to calculate power from Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA2) [34], and the regional forecasting model of High-Resolution Rapid Refresh (HRRR) [35] from a tool called PLUSWIND. The data is publicly available for 2021 weather outputs and capacity factors of each individual wind turbine. For PV plants' output power validation, the capacity factors from [12], [13] in a tool called Ninja are used as a benchmark. Both of these references, provide detailed data for PV power outputs and weather-informed hourly capacities at any point in the world using

TABLE III:
Validation and characteristics of Solar Generation

EIA Plant Code	Capacity (MW)	Tracking	Calculated (MWh)	MERRA2 (MWh)	Diff MERRA2 %	Corr MERRA2	Location
63255	420	1-Axis	505996	446422	-13.3	0.79	TX
62755	300	1-Axis	535092	546188	2.0	0.88	TX
65271	275	1-Axis	434511	428876	-1.3	0.87	TX
63320	260	1-Axis	247855	331225	25.2	0.81	TX
62483	255	1-Axis	165694	173877	4.7	0.75	TX
62804	255	1-Axis	162795	176724	7.9	0.77	TX
57378	253	1-Axis	571312	462846	-23.4	0.92	CA
61202	252.3	None	464088	410645	-13.0	0.89	NV
63504	252	None	137779	185093	25.6	0.73	NV
57859	250	1-Axis	436746	409463	-6.7	0.89	CA

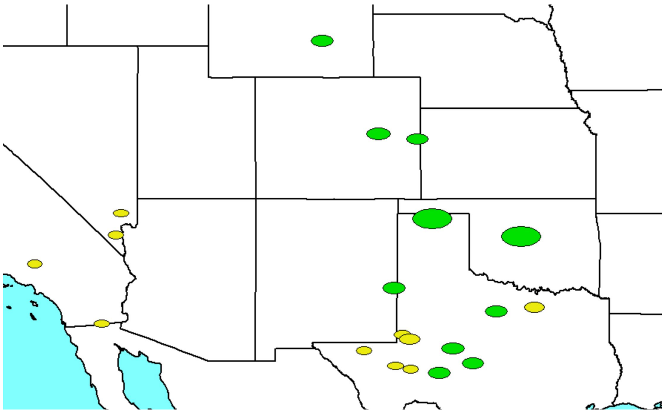

Fig. 3: Location of the studied large wind (green) and solar (yellow) power plants in North America

MERRA2 weather data. The solar irradiance data gathered from MERRA2 weather data is converted into power outputs of PVs using the Ninja tool [36].

IV. Validation of Methodology

Previous work [37] validated the calculated renewable data at the utility and aggregated state level. This study focuses on individual renewable plants for a more precise validation and shows the results for the largest wind and solar plants in the U.S. The validation process involves comparing the published power plant scale wind and solar generation data with calculated values derived from ERA5 weather data and integrated into the power system model.

Utilities do not disclose the detailed hourly output data of individual generators over the years. However, we compare our proposed strategy with the latest available resources in the literature. For wind data validation reference [14] is used and for solar data validation, the output data are compared to [13].

In Table I, a comparison of wind generation for the largest wind-producing wind farms is presented based on their overall generation in 2021. The calculated wind generation is compared with the results from MAERRA2 and HRRR presented at [14] and the correlations between hourly wind turbine outputs of the calculated results and each of these two resources are compared. The results show a high correlation above 0.5 and the annual differences between the calculated generation and the studied references are usually below 35%. The discrepancies between the calculated and reported figures can be partly attributed to factors such as the absence of curtailment in the calculations. Also, the selected largest wind turbines are mapped to the closest available wind turbine in 2021 generation data so the locations of mapped turbines can be slightly different. Also, in general, as shown in Table I and mainly in mountainous areas, the wind at the wind turbine's actual hub height can be different than the studied wind speed from ERA5, which is 100 meters above the ground. Moreover, the values of hub height in PLUSWIND are limited to 91.44 meters. Table II shows the characteristics of the studied wind turbines such as their location, EIA plant code, installed capacity and their hub heights.

Table III compares calculated and available solar PV generation for the top ten largest solar farms and compares the annual correlation of these values. The results show a high correlation of above 0.7 and an overall difference of below 25% based on 2019 weather data. The Table also shows the main parameters of PV plans including EIA plant code, capacity, location, power point tracking type, and the used tilt angle and azimuth angles. However, there are some differences in the parameters of PVs based on EIA–860 generation data in 2022. The U.S. EIA's report [38] on installed capacities and types of renewables is a key resource for validating renewable generation capacity calculations since the parameters of the generators should match. For example, the Ninja reference does not include tilt angle tracking for one-axis values and elevation tracking but only includes one-axis azimuth tracking, two-axis tilt and azimuth tracking models and fixed angles with no tracking. Also, the studied Azimuth Angle in the EIA–860 data is usually entered as zero or blank so approximation values are used. On the other hand, Ninja website considers losses for PVs so 10% to 20% losses are considered for PV outputs. However, the proposed methodology uses a more precise model including the inverter loading ratio with a typical DC-AC ratio of 1.25.

V. Summary and Future Work

In this study, we developed a methodology for calculating the generation capacity and power outputs of wind and solar power generators based on ERA5 weather data, including temperatures, dew points, wind speed and wind direction at the surface and 100 meters height, radiation and cloud coverage. This approach utilized information from the 2022 EIA–860 form and data from numerous weather stations across the United States. The main benefit of this strategy is the ability to study all historical weather scenarios and their impact on the current power system. The proposed methodology is versatile and can be applied to any set of generators where local weather data is accessible. Such weather-based scenarios are deemed crucial for future network planning, especially considering the expected increase in renewable energy adoption. The ultimate goal is to enhance the resilience and robustness of power systems in the face of changing weather patterns and increasing reliance on renewable energy sources.

The calculated generation capacities of individual renewable energy sources are then compared and validated against available generation data from the literature, specifically focusing on the top largest renewable plants in the U.S. The study found a close correlation between the generation values of calculated and available references for most of the generators, though some deviations were observed in certain cases mainly due to the differences in power models and parameters.

VI. Acknowledgements

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