Developing a Dashboard To Enhance Visualization of Similar Historical Weather Patterns and Renewable Energy Generation

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Figure 1: Screenshot showing the Historical Weather & Renewable Energy Insights panel where the five sections are alphabetically labeled. A: Static image of the substation layout on the geographic footprint of Texas; B: User-selectable inputs (date, metrics by which to find similar days); C: Outputs with the three most similar days to the selected date; D.1: Weather profiles for user-selected metrics by which similarity is calculated; D.2: Rest of the weather profiles for the four days; E: Wind and Solar generation output.

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Abstract

This paper presents a dashboard to find and compare days with similar weather patterns within an 80-year historical weather dataset. The dashboard facilitates the analysis of weather patterns and their impact on renewable energy generation by defining and identifying

similar weather days. Users are given the flexibility to select the metric for determining similarity, which includes a combination of temperature, dew point, wind speed, Global Horizontal Irradiance (GHI), Direct Horizontal Irradiance (DHI), and cloud cover. The region for this work is limited to Texas. The dashboard then generates an output that compares the selected weather metrics and the corresponding renewable generation outputs.

Index Terms: Visualization, Weather, Power Grids, Dashboard

1 INTRODUCTION

Weather patterns demonstrate cyclic behavior due to various seasonal and climatic factors. Since the power system is becoming more dependent on renewable resources, recognizing these cycles is essential for predicting the potential impact of weather conditions on renewable energy generation and the power grid. By analyzing historical weather data, it is possible to identify recurring patterns and trends, which can then be used to create scenarios for different weather conditions with a certain degree of accuracy or reliability, given that these patterns have occurred before and are likely to recur. This cyclic nature of weather also highlights the importance of using historical data for future days to plan for a grid that can withstand extreme weather scenarios.

The cyclic nature of weather patterns has been considered in the literature. Reference [1] discusses cyclic weather patterns by examining how these patterns contribute to and interact with climate variability, ultimately impacting both environmental conditions and human activities. Researchers of [2] examine and analyze cyclic weather patterns in Australia using statistical methods to identify and understand periodic trends and their impact on regional climate variations. Royal Meteorological Society investigates cyclic weather patterns by utilizing climatological data and statistical analyses to identify and interpret periodic climate phenomena and their implications on weather variability in [3] considering their impact on weather predictions based on European weather data.

Reference [4] examines and analyzes cyclic weather patterns by reconstructing historical climate data and employing statistical methods to identify recurring climatic trends and their impacts on Slovakia's weather variability. Reference [5] studies the public perception of climate change and weather patterns through surveys and statistical analysis to understand how individuals interpret cyclic weather phenomena and their relationship to climate variability. Reference [6] explores cyclic weather patterns by analyzing the geographic effects of weather cycles on soil erosion and landscape formation, using empirical data and statistical methods to identify and quantify these cyclic influences. However, most studies on cyclic weather patterns focus on the weather measurements and not on their impact on the power system.

The impact of weather measurements on the power system has attracted attention through the direct inclusion of historical weather data in planning and forecasting, which offers significant benefits, particularly in the context of renewable energy generation. [7] Historical data provides a rich source of information about past weather conditions, which can be used to anticipate future weather scenarios. By leveraging this data, our understanding of power grid behavior under different weather scenarios can be enhanced to make informed decisions about grid management. This approach allows for better preparedness and optimization of renewable energy resources, contributing to stable and reliable power grid operations.

While multiple weather data dashboards are available (a search on GitHub returns 157 results) [8], there is a growing interest in understanding and visualizing the direct impact of weather conditions on power grid performance. Additionally, future-looking weather has already been used for load forecasting [9, 10]. Existing research emphasizes a need for more comprehensive studies that not only compare weather data but also analyze its implications on the power grid performance. Understanding these impacts is essential for developing strategies to mitigate adverse effects and optimize the integration of renewable energy sources into the grid.

Incorporating weather data into power grid analysis involves examining how different weather conditions affect energy generation, particularly from renewable sources like solar and wind. Identifying days with similar weather patterns allows studying corresponding power generation outputs to determine the correlation between weather conditions and energy production. This analysis aids in developing predictive models that forecast renewable energy output based on expected weather conditions, thereby improving the efficiency and reliability of the power grid.

The cyclic nature of weather, the benefits of using historical weather data for future planning, and the need for more comprehensive studies on the impact of weather on the power grid motivate this work. The goal of this paper is to create a dashboard that visualizes the impact of historical weather on the current power grid. In this work, we show results using the synthetic 7,000 bus case on the geographical footprint of Texas. Such a dashboard is essential for achieving a comprehensive understanding of weather-related influences, as it enables clear analysis and comparison, providing insights into how past weather conditions could have influenced energy outputs.

2 BACKGROUND

Initial work on directly including weather in optimal power flow (OPF) is explained in [11]. As highlighted in [12], numerous weather datasets are available for planning purposes, each possessing key attributes such as 1) inclusion of essential variables, 2) coverage spanning multiple decades with ongoing updates, 3) consistency and physical coherence, 4) validation, 5) proper documentation, 6) regular physical updates, and 7) accessibility. Notable examples include the European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis fifth generation ERA5 [13], NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA) and its update MERRA-2 [14], the High-Resolution Rapid Refresh Model (HRRR) [15], and specialized resources like the WIND Toolkit [16]. Each dataset has its unique advantages and limitations [17], and they can be integrated into an efficient file format developed for modeling, loading, and storing of any number of time and spatially varying weather scenarios or extreme events called PWW format with the latest documentation details available at [18]. This paper does not promote a specific format or data source but emphasizes the broad availability of these datasets. Both near-term forecasts (e.g., from [19]) and long-term data [20] can be utilized.

For this work, the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis of generation (ERA5) weather measurements relevant to the power system, including variables such as temperature, dew point, wind speed, and direction, cloud cover percentage, and solar irradiation values has been processed. These data are utilized at each 0.25 degrees of latitude and longitude for historical data from 1940 to the present to model future Environmental Inputs (ENIs) by leveraging historical weather patterns.

Power flow weather (PFW) models are created to model the impact of weather measurements on the power grid components. To create PFW models, wind speed has been correlated with the output power of wind turbines based on their classes from the EIA-860 data. For solar generation, Global Horizontal Irradiance (GHI), Direct Horizontal Irradiance (DHI), cloud coverage, and photovoltaic characteristics have been used from the EIA-860 data, such as tilt angle, azimuth angle, and tracking type.

PowerWorld Weather (PWW) files containing all relevant weather data from 1940 to the present have been generated and are available at [18] website. The data has also been validated at [21] to ensure that the PFW models reflect the weather-related impacts on the power grid. Of note is that since real-world power grid information is considered Critical Energy Infrastructure Information (CEII), this work uses the synthetic copper plate model generated using EIA-860 data to get the renewable energy generation outputs that are mapped to the synthetic generator locations [22].

For specific studies such as identifying renewable resource droughts, graphs with each point of them showing the average, minimum and maximum of all historical data are created as shown in [23] and [24].

3 Weather Data Analysis and Methodology

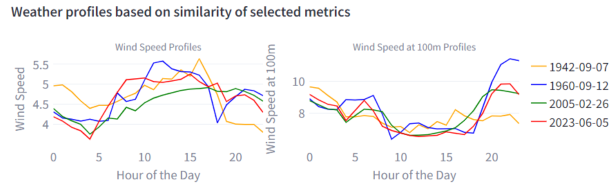
This study aims to develop a dashboard to identify days with similar weather patterns. An essential aspect of this research is investigating whether days with similar weather conditions yield comparable renewable energy generation outputs. Determining the criteria for similar weather conditions is essential to achieving this objective.

Utilizing data from ERA5 [13], meteorological parameters for each station in the United States, including temperature, dew point, GHI, DHI, cloud cover percentage, wind speed at the earth's surface, and wind speed at 100 meters from the Earth are considered. Based on the specific analysis requirements, user input is obtained to determine the relevant criteria for identifying similar days. The selection of weather parameters can be refined based on their correlations. For instance, temperatures and dew points are considered together, wind speed at the surface and wind speed at 100 meters are grouped, and finally, the cloud cover percentage, GHI, and DHI are analyzed together. This collective analysis is used to find similar days concerning 1. Temperature and Dew Point, 2. Wind Speed at the surface and Wind Speed at 100 meters, and 3. Cloud Cover, GHI, and DHI. An additional option is considered where days with similar weather patterns can be found in the context of all-weather metrics, i.e., 4. All measurements.

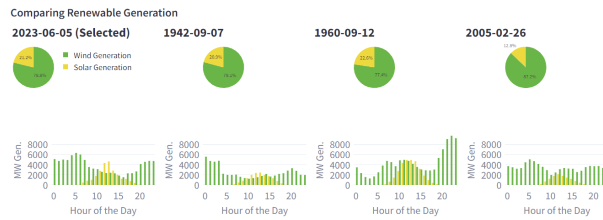
This study employs two primary methods to identify past days with weather conditions similar to any selected day. These are either using Frobenius norm[25], or principal component analysis (PCA)[26]. The choice of method depends on the application and involves a trade-off between output accuracy and computational efficiency. The two approaches are matrix search and dimensionality reduction. These methods are discussed in the supplementary material. Of note is that this work's geographical region is limited to Texas. However, ultimately, the goal is to use the same methodology to develop the tool for the entire United States to provide users with a choice of selecting the region for a better analysis.

4 Dashboard

[27] recommends a systematic methodology for the development of dashboards, structured into four distinct levels: initial characterization of tasks and data using the terminology specific to the problem domain, abstraction of these elements into operations and data types, design of visual encoding and interaction techniques, and the development of algorithms to implement these techniques efficiently. In the context of our work, the process begins with identifying historical days that mirror a given day in terms of five/selected weather metric profiles to evaluate changes in renewable energy generation. The abstraction phase employs various data types and visualization methods, including dropdowns for selection, textual outputs, tabular displays for results, line graphs for comparative analysis of weather metrics, pie charts for generation data, bar charts for hourly representations, and heat maps for data correlation. Visual encoding and interaction designs are predominantly executed using Python, leveraging libraries such as Plotly[28] and Streamlit[29] to enable dynamic visualizations. The algorithmic stage focuses on efficiently processing and visualizing data in response to user interactions and choices, ensuring that the insights derived are pertinent.



(a) Wind speed profile.



(b) Solar and wind generation output.

Figure 2: Comparison of a. Wind speed profiles and b. Solar and wind generation output on selected day + three similar days with selected day: 2023-06-05 and selected metric: wind speed.

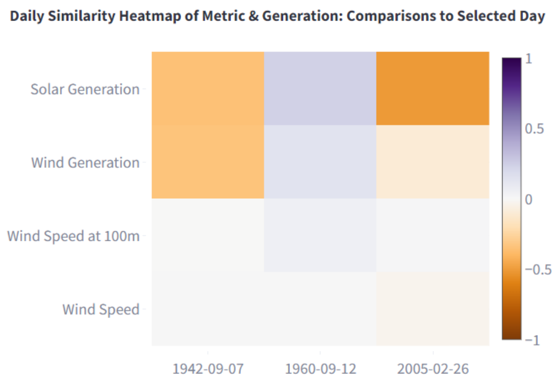
This dashboard is divided into five key sections. The first section, ***A***, is just a static image of the substation layout for the case that is considered. This will change depending on the location of the data we look at. At this point, the dashboard outputs are limited to the Texas region. For this work, we use a synthetic 7,000-bus power grid model on the footprint of Texas. This test case has been validated against the metrics derived from the North American power grids (cite Dr. B). The dots represent fictitious locations of the solar (yellow) and wind (green) generation.

Section ***B*** is the user input section, allowing users to select a date and a metric to identify similar days. The choice of metric is a dropdown box with the following options: *All measurements*, *Temperature and Dew Point*, *Wind Speed*, *GHI, DHI, and Cloud Cover*. The choice of coupling of metrics has been made based on a higher correlation of specific weather parameters such as temperature and dew point, GHI, DHI, and cloud cover. The user also has a choice to determine similar days based on all weather parameters mentioned above. Another user input is the date. This is a calendar format wherein the user can select a day to find other days similar in the selected weather metric to the user-selected day. The date ranges from January 1, 1940, to December 31, 2023. The goal is to update the background data as frequently as the release of weather data so that the user can select the most recent days as well. Finally, upon clicking on the ***Find Similar Days*** button, all results and plots are generated.

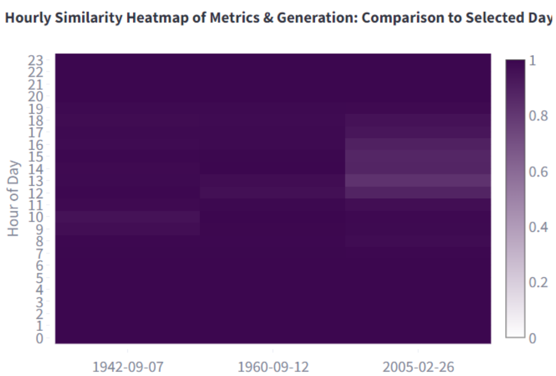
Section ***C*** shows the output in a list format, ranking all the closest days to the selected date right below the ***Find Similar Days*** button. This also shows the mean absolute percentage error (MAPE) values for the selected metrics of all three similar days to those of the selected day. The fourth section is subdivided into two: ***D.1*** and ***D.2***. This is the output section, where the chosen metrics are compared using line plots. ***D.1*** shows the 24-hour profiles for the metrics used to determine the three similar days. Whereas ***D.2*** shows the remaining 24-hour profiles for the rest of the metrics. This way, the differences or similarities of all the metrics can be observed.

It is important to note that the algorithms in this work identify similar trends in the weather profiles over a day in a specific region, i.e., Texas. For example, for the selected day of 2023-06-05, the generator outputs are shown in Fig. 2b with the wind profiles shown in Fig. 2a. Even though the three closest days have similar profile shapes over the 24 hours, the wind generation output for these days differs, with the highest production on 1960-09-12.

Below section ***D.1*** is section ***E***, which compares the renewable generation output for four days (the selected day and the three closest days). Four different types of plots are used to understand the key differences. Pie charts show the contribution of solar and wind generation for a day. The bar chart shows time series information and a generation distribution for all 24 hours. Heat maps quantify how similar the three days are to the selected day.



(a) Comparison by day.



(b) Comparison by hour.

Figure 3: Heatmap comparison of a. By day and b. By hour on the selected day + three similar days with selected day: 2023-06-05 and selected metric: wind speed.

The heat maps in Fig. 3 provide a comparative analysis of two types of information, aiming to assess the similarity between the output days and the selected day. In Fig. 3b, the vertical axis represents the hours of the day, spanning from 0 to 23. Conversely, in Fig. 3a, the vertical axis represents the metrics used to identify similar days, along with wind and solar generation data. The horizontal axis in both heat maps displays specific dates, each corresponding to the output day most analogous to the selected day. The color scale for the daily heat map in Fig. 3a ranges from -1 to +1, explicitly designed to indicate the degree of similarity in generation relative to the selected day, whether lower or higher. However, in Fig. 3b, the color scale ranges from 0 to 1, as it exclusively measures the magnitude of the difference between the output days and the selected day on an hourly basis, considering all metrics and generation values collectively.

The normalized box plots visualize the values of the chosen days relative to all the historical weather data and their renewable generation outputs, respectively. The seven weather metrics for the 80-year dataset and their application to two renewable generation output values (using PFW models based on the latest EIA860 copper plate model) over the same period have been normalized and visualized using nine box plots. The values for the four days are also shown as positions on the box plot, visualizing where they lie relative to the mean, median, and outliers. Fig. 4 visualizes this information for the selected day, 2023-06-05, and the three similar days: 1942-07-09, 1960-09-12, and 2005-02-26.

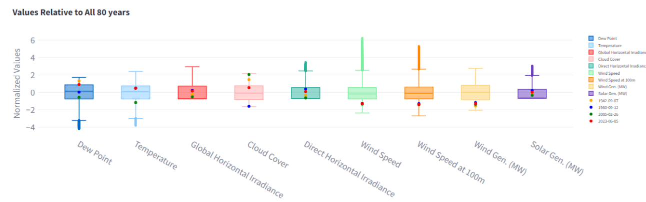


Figure 4: Comparison by metric against all 80 years and the four days (selected day + three similar days).

5 Case Study

In this case study, September 8, 2023, is selected as a representative example, as it recorded the highest temperature in Lubbock, Texas, during the year 2023 [30]. Table 1 shows the three similar days identified based on different metrics for this selected day.

Table 1: Three most similar days to 2023-08-08

Temp Dew Point	Wind Speed at 10m, 100m	GHI, DHI & Cloud Cover	All metrics
1948-06-08	1945-09-08	1976-09-12	2000-09-11
1958-06-08	1985-09-08	2012-09-05	2012-09-07
1988-06-08	0988-09-08	2023-09-06	2012-09-05

The supplementary materials provide snapshots of the dashboard results. Table 2 shows the output generation for similar days calculated based on the chosen metric. Irrespective of the weather metric selected, the solar generation on September 8, 2023, was 29,564 MW, while wind generation reached a notably high 267,095 MW. When looking at only temperature & dew point, the wind generation showed significant variability across different dates, ranging from 184,779 MW on June 8, 1948, to 356,641 MW on June 8, 1958, suggesting significant variations in wind speed on these days. When looking at only specific wind speed conditions at 10m and 100m heights, with wind generation varying from 217,863 MW on August 9, 1985, to 252,475 MW on August 9, 1988, while solar generation remained within a narrower range of 29,387 MW to 30,229 MW closer to the solar generation output of September 8, 2023.

When only considering GHI, DHI & cloud cover, wind generation ranged from 132,287 MW on September 6, 2023, to 350,879 MW on September 12, 1976, and solar generation varied slightly between 28,760 MW and 29,203 MW. Finally, when looking at aggregated data across all metrics, it is seen that wind generation fluctuated between 182,672 MW on September 5, 2012, and 291,160 MW on September 11, 2000, while solar generation remained relatively stable, ranging from 28,865 MW to 29,203 MW. This analysis underscores the variability in wind power output influenced by different weather conditions, while solar power output remains more consistent across varying metrics.

As also illustrated on the dashboard snapshots in the supplementary material, the three selected days are compared with the reference day to assess their similarities and differences. The extracted data for this comparison is presented in Fig. 5. In Fig. 5a and Fig. 5b, the differences in the weather metrics are minimal, with values close to zero. However, Fig. 5c shows the most considerable

Table 2: Renewable generation output based on EIA860 generator data for 2023-09-08 and the three similar days based on (a) temperature & dew point, (b) wind speed, (c) GHI, DHI & cloud cover, and (d) all metrics considered together.

(a) Temperature & Dew Point

Date	Solar (MW)	Wind (MW)
2023-09-08	29,564	267,095
1948-06-08	24,944	184,779
1958-06-08	24,298	356,641
1988-06-08	24,217	237,185

(b) Wind Speed

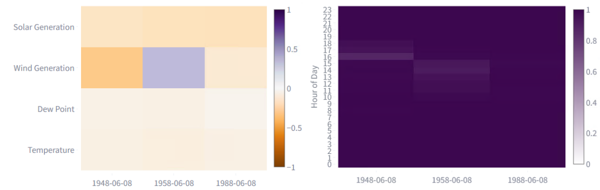
Date	Solar (MW)	Wind (MW)
1945-08-09	29,387	244,253
1985-08-09	29,807	217,863
1988-08-09	30,229	252,475

(c) GHI, DHI & Cloud Cover

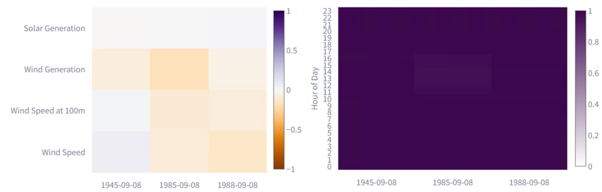
Date	Solar (MW)	Wind (MW)
1976-09-12	29,138	350,879
2012-09-05	29,203	182,672
2023-09-06	28,760	132,287

(d) All metrics

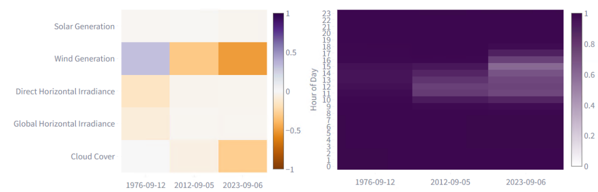
Date	Solar (MW)	Wind (MW)
2000-09-11	29,185	291,160
2012-09-07	28,865	240,070
2012-09-05	29,203	182,672



(a) Temperature & Dew Point



(b) Wind Speed



(c) GHI, DHI & Cloud Cover

Figure 5: Heat map showing the similarities by metrics, days, and hours.

discrepancy observed in cloud cover. These findings are consistent with the Mean Absolute Percentage Error (MAPE) values calculated for these days, indicating that cloud cover may not be the most reliable metric for matching days in this analysis or a more accurate threshold is required to find similar days based on cloud cover. The differences observed in the solar and wind generation values for the three heat maps in Fig. 5 match the observed values in Table 2 with the most variation observed in wind generation.

Table 2 and Fig.5 demonstrate how different weather conditions can significantly influence solar and wind power generation, as captured by specific metrics. Wind power, in particular, shows a broader range of variability than solar power, which remains more consistent across different metrics and dates. This variability emphasizes the importance of understanding and predicting weather patterns for optimizing renewable energy generation.

6 Conclusion and Future Work

The paper presents a platform for analyzing historical weather data and their impact on renewable energy generation. A crucial aspect of this study is defining the interpretation of similarity, which can be approached in various ways. The discussion also shows how days with similar weather metrics can differ in their renewable generation outputs using weather and generator models.

Some examples are provided for each of the available metrics, in addition to some interesting real-world weather events that have been found to occur. Future research will explore improved methods to calculate similarity, explore multiclass classification, and include wind direction as an additional metric. Eventually, the goal is to extend the capabilities of this dashboard to the entire United States. The code used in this work is publicly available in a GitHub repository at [31].

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