Power Flow Modeling of the Impacts of Weather and Other Resiliency Hazards With a Focus on Transmission Planning

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Abstract—**This paper presents an approach for modeling weather and other environmental inputs (ENIs) in the power flow and related tools with a focus on electric grid transmission planning. Such work is needed because of the rapidly growing dependence of electric grids on the weather and the need to consider the impact of more severe resiliency events. The paper presents a modeling approach, and then demonstrates it using several large-scale electric grids. Validation is also considered. A key contribution is to show that environmental inputs can be directly integrated into existing power flow and related tools such as contingency analysis and optimal power flow.**

I. INTRODUCTION

The purpose of this paper to present an approach for modeling weather and other hazards in the power flow, with a particular focus on providing readily implementable solutions for electric grid transmission planning. As defined by the North American Electric Reliability Corporation (NERC) [1], Transmission planning (Planning Assessment) for large-scale electric grids is, the "Documented evaluation of future transmission system performance and corrective action plans to remedy identified deficiencies." This planning considers timeframes ranging from near real-time to decades [2].

While transmission planning has always been challenging, it is easiest when integrated with the design of new controllable generation and when the anticipated load can reasonably be estimated [3]. It is much more challenging under the conditions that now exist in many locations where new generation is not directly planned, and large amounts of wind and solar generation are making the grid much more weather dependent. Further challenging planning is the growing desire to enhance the resilience of electric grids to a variety of potentially disruptive events [4]. The most important planning tools are the power flow, and related applications such as optimal power flow (OPF) and contingency analysis. The goal of this paper is to improve planning by expanding these tools to more directly model the impacts of weather and other resiliency hazards.

The power flow is a steady-state analysis tool that assumes an electric grid is operating at a constant frequency. The tools used in transmission planning usually assume a perfectly balanced three-phase grid and uniformly transposed transmission lines, allowing for the solution of a simpler positive sequence model. In its simplest form the key power flow input variables are 1) the real power values for the generators, 2) the generator setpoint voltage magnitudes, 3) the real and reactive power values for the loads, and 4) the transmission line and transformer (branch) statuses. The power flow then calculates all the bus voltage magnitudes and angles, allowing for the power flows on all the branches to be calculated. With assumed branch limits, the percentage loads can be determined. The OPF extends the power flow by allowing some of these inputs to vary, such as the generator real power values, to do an optimization, usually minimizing generator cost subject to variety of constraints including the branch flow limits.

The electric grid, and by extension the power flow, can be directly impacted by weather and other resiliency hazards such as earthquakes, wildfires, geomagnetic disturbances (GMDs) or volcanic events. Here these external events are referred to as environmental inputs (ENIs). Direct power flow modeling of ENIs requires making some of its parameters functions of one or more ENIs.

Which ENIs should be included is problem dependent. However, some are much more generically applicable than others. For example, with many grids now having large amounts of wind and solar generation, whose outputs are inherently ENI dependent, at least some weather information (e.g., wind speed, insolation, cloud cover, temperature) should usually be included. To deal with other weather-related events, such as hurricanes, ice storms, or derechos, this information could be expanded to include wind gusts, and precipitation. Other events such as earthquakes, wildfires, geomagnetic disturbances (GMDs) or volcanic events would require additional ENI datasets. This paper presents a general approach for handling a wide variety of ENIs, with more specific coverage of weather-related events.

As is the case with any engineering analysis tool, directly modeling ENIs in the power flow involves tradeoffs between factors including accuracy, complexity, problem scope, and model parameter availability. This is recognized in the well-known quote, "Remember that all models are wrong; the practical question is how wrong do they have to be to not be useful" [5]. Such tradeoffs are just an extension of what has already been done for decades with power flow design. For example, while three-phase power flow formulations are well-known [6], the simplicity benefits of the positive sequence approach usually outweigh any potential three-phase benefits. Similar tradeoffs exist with ENI modeling. For example, how much accuracy is needed with weather inputs such as wind speed or insolation, or how much detail is needed to model the impact of an eclipse on solar generation [7]. These issues are considered later in the paper, with a specific focus on the requirements for transmission planning.

An implicit assumption in this approach is the availability of geographic coordinates for all the electric grid components of interest. While this information had not been historically included with many power flow models, now it is either directly available, or fairly easily obtainable at least at the electric substation level. Examples of planning model manuals specifying the need for substation latitude and longitude include [8] and [9].

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The paper results are demonstrated using three large electric grids. The first is a 6717 bus (7K), 345/138/69 kV synthetic grid covering most of the US state of Texas [10], [11]. Its oneline is shown in Figure 1. The second is a synthetic 23,643 bus (24K) grid covering much of the central part of the US [12]. The third is a series of copper plate [13] grids developed using US Energy Information Administration Form 860 (EIA-860) [14] data that provides information on all generators in the US larger than 1 MW, including their geographic location [7]. Figure 2 visualizes the wind and solar generation from the EIA-860 grid developed using installed generation at the end of March 2024 using the geographic data view (GDV) approach [15]. In the figure the green ovals show the wind and the yellow ovals the solar generation, with the oval size proportional to the installed capacity. All of these grids are publicly available at [16].

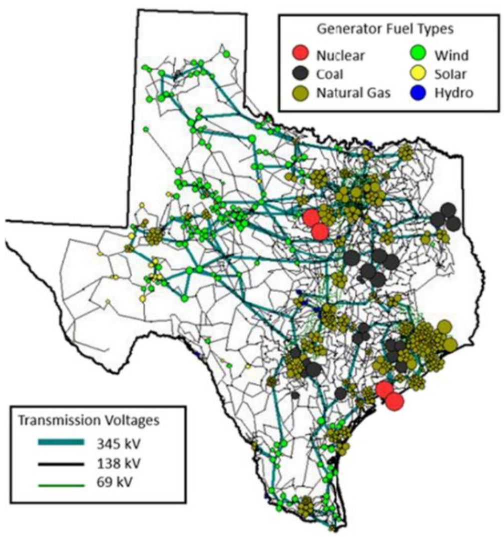

Figure 1: Texas 7K Synthetic Grid Oneline

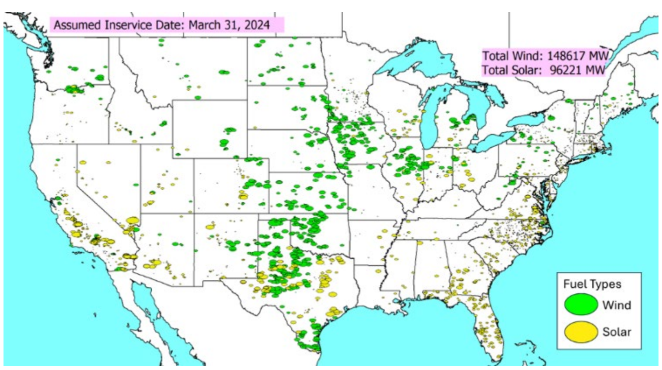

Figure 2: EIA-860 Case Wind and Solar Maximum Capacity (Q1, 2024)

The remainder of the paper is organized as follows. The next section presents the approach integrated into a discussion of prior work in the area. Then Section 3 addresses how the approach can be validated. The following section provides some specific examples, while Section 5 provides some future directions. All calculations and visualizations are done with PowerWorld Simulator Version 23.

II. Approach

Incorporation of ENIs into the power flow requires consideration of two main issues. First, additional models are required to represent the impact of the ENIs on the power flow component models. Second, the ENIs need to be adequately represented over the electric grid footprint of interest including each impacted device. This section addresses each of these issues. The approach presented here builds on the large amount of prior work in the pertinent domains, with the paper's particular focus being providing an approach that can, and to some extent already has been, implemented in commercial transmission planning software.

For the first issue, the modeling methodology presented here builds on the prototype approach from [17]. That is, to imitate the electric grid stability modeling approach in which a variety of model types are used to represent different system devices (e.g., load models, machine models, governors, line relays, etc.). When digital stability programs first appeared around 1960 the number of available models was quite small, all associated with the synchronous generators [18], and then over the years the number grew and became more standardized. Now stability software vendors support many 100's of different models covering an expanded number of electric grid object classes (e.g., synchronous generators, renewable generators, loads, HVDC lines, relays, etc.). In a similar manner the initial set of models needed to represent the electric grid impacts of ENIs in the power flow would start small and grow as the needs expand.

Using the naming from [17], these new models are referred to as PFW Models ("power flow weather" or more broadly "power flow whatever" models). The PFW models can be quite simple, such as setting a wind generator's maximum power output based on its hub height wind speed and its wind power curve (WPC), or solar PV output based on the Global Horizontal Irradiance (GHI) and Direct Horizontal Irradiance [19]. They could be of medium complexity, such as transmission line ambient-adjusted ratings [20], dynamic transmission line ratings [21], or the variation of thermal generator's power output based on their ambient output temperature [18]. Or they could also be more complex, such as setting a transmission line's limit based on weather along its right-of-way including potentially different limiting devices.

These models could also be stochastic. For example, modeling the likelihood that electric load at a bus would be lost due to a variety of different weather or other ENIs, the failure of substation equipment or transmission lines due to an earthquake, the availability of virtual power plants (VPPs), the restoration time for devices, or the increasing likelihood of generator failures during cold temperatures [22], [23]. For both deterministic and stochastic classes many such models do already exist in the literature, with others still needing to be developed. For example, [24] discusses failure probabilities of power system assets. Validation, covered in the next section, is also important.

A consideration in the development of the PFWs is the availability of potential parameters versus the required accuracy. For example, in the US the Energy Information

Administration Form 860 (EIA-860) [14] provides information on all generators larger than 1 MW, including their geographic location. For the wind generators the EIA-860 also gives their turbine manufacturer and model, hub height, wind quality class (ranging from Class 1 for high wind to Class 4 for very low wind), and the design wind speed. In developing the wind generator PFW models the availability of this information has been considered by including generic models for each of the wind quality classes using data from [25], and then also including a PFW model in which the individual points on the WPC can be specified. Detailed WPCs for all of the EIA-860 wind turbines (2020 data) is available at [26]. Figure 3 shows the WPCs for the four generic types, while Figure 4 compares the detailed WPC for a large wind turbine (EIA 860 Plant ID 60619) with its generic Wind Class 2 model. While not considered here, more advanced PFW models could be defined that include other inputs such as temperature dependence in the WPC [27].

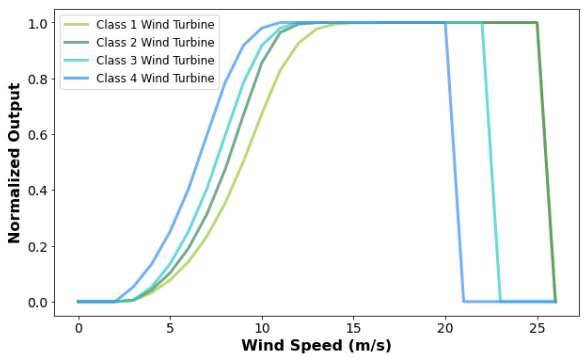

Figure 3: Wind Turbine Class PFW Models [25]

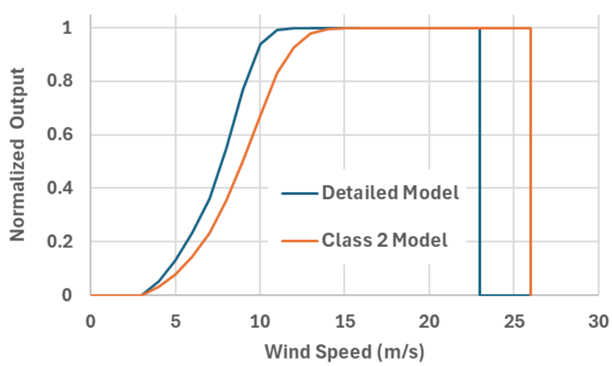

Figure 4: Comparison of Detailed and Class 2 Wind Turbine PFW Models

For solar cell models, the main parameters include the installed capacity of real power, the type of solar PV tracking (fixed, single-axis, dual-axis), the azimuth, the tilt angle, and an assumed sky diffuse). The solar model estimates PV generation using local solar radiation, or the standard equations for insolation based on location and time of day including cloud cover which is combined with the solar power point tracking model to determine the sun's tilt and azimuth angles [19]. The input of the inverter loading ratio [28] is also included. This ratio models 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 [29, 30]. 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.

The second main issue associated with ENI modeling in the power flow is ensuring it is adequately represented over the electric grid footprint of interest. How much detail is required depends on the particular ENI, and how much accuracy is needed or even possible in determining the power grid inputs. From a power flow perspective, the ENIs can be grouped into two major classes: 1) those that inherently interact with the electric grid and hence require additional modeling, and 2) those that do not. Examples of the first include modeling the impact of the quasi-dc geomagnetically induced currents (GICs) caused by either a geomagnetic disturbance (GMD) [31], [32], or a high altitude electromagnetic pulse (HEMP) [33], [34], and the modeling of temperature induced changes to the branch resistance in which the change depends not only on the ambient weather but also the branch flow [35]. Most ENIs are in the second group, such as weather, earthquakes, wildfires, and volcanic events. That is, these are events that can impact the electric grid, but the electric grid doesn't particularly influence them.

The PFW approach can be used with both classes, though the focus in this paper is on the second, with a particular emphasis on weather. Still, before going further it is useful to briefly consider the integration GMDs into the power flow as a case study of what this paper advocates can be done with many ENIs. GMDs have been known to impact electric grids by causing GICs since the 1940's, with research grade software integrating GMDs into the power flow presented about 40 years later [31]. Over the next 30 years to the extent GICs were included in the power flow it was done through external calculations [36]. Then with concentrated industry focus [32] GMDs began to be integrated into commercial power flow software [37]. Now, at least in North America, all of the major power flow vendors have GMD add-ons that take the GMD ENIs (i.e., an electric field with temporal and spatial variation), calculate the associated GICs, and then use models to determine the power system impact. This has helped in the development of standards for GMD assessment [38].

Currently most other ENIs are being considered in the power flow either at the research level or through external calculations, such as to determine wind generator power outputs or the iterative approach of [24], with the results then imported into the power flow. The premise here is that much of this can be done in a straightforward manner within power flow packages. Key to this is having an easy ability for the power flow to access a spatial-temporal model of the ENIs. The approach used here is to leverage what is already done with GMD analysis and use a single file format for loading the ENIs. This format, known as PWW ("PoWer Weather," or "PoWer Whatever") files, allows easy modeling of any number of time and spatially varying ENI quantities in a public format [39] (with the latest documentation at [40]).

For example, to model the weather impacts on the grid (e.g., wind and solar generation or transmission line limits) the PWW file contains values such as temperature, dew point, wind speed and direction, wind gusts, cloud cover percentage, and if available solar irradiation values. As noted in [41] there are a number of weather datasets available that could be used for planning, with the main desired attributes being 1) including the necessary variables, 2) covering multiple decades with ongoing extension, 3) coincident and physically consistent, 4) validated, 5) documented, 6) physically refreshed and 7) available and accessible. Example datasets include The European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis fifth generation ERA5 [42], the National Aeronautics and Space Administration's Modern-Era Retrospective Analysis for Research and Applications (MERRA) (or MERRA-2 which is an update of MERRA) [43], the High-Resolution Rapid Refresh Model (HRRR) [44], and more specialized products such as the WIND Toolkit [45]. All of these have their strengths and weaknesses [46], and their data could be modeled using the PWW file approach. This paper's purpose isn't to advocate for a particular format, rather just to indicate wide availability. Forecast data could also be used, either near-term forecasts (e.g., from [47]) or longer-term data [48]. The weather results presented in the remainder of the paper are done using ERA5 data, which has a spatial resolution of 0.25 degrees (roughly 31 km), with values for most of North America going back to 1940 in the PWW format available at [40]. The wind generation examples presented here use ERA5 10m and 100m wind speed to estimate the hub height speed. The impact of spatial resolution on planning is considered in the next section.

Other ENIs including earthquakes, wildfires and volcanic eruptions could also be considered using this approach. For example, with earthquakes useful background modeling is presented in [49] and [50], and one likely useful earthquake dataset is at [51]. For events in which there is a coupling of more than one ENIs separate PWWs could be used to represent each separate event with their results combined. For example, considering the impact of hypothetical wildfire smoke on solar generation coupled with historical irradiation values, with the conclusion of [52] is that "wildfires can significantly attenuate the solar radiation at both short downwind distances as well as far from emissions sources." By creating PWWs that represent the spatial and temporal variation in the smoke from either past or hypothesized future events, planners could consider wildfire smoke risk in their designs. A purpose of this paper is to help the transfer of such research results into planning practice.

An example of such modeling that has already occurred is the representation of the October 14, 2023, annular eclipse and the April 8, 2024, total solar eclipse on the US solar generation. Both events were modeled a priori with the PFW approach by combining solar irradiation data (both clear sky and using assumed cloud cover) with a representation of eclipse. Figure 5 shows a visualization of the April event in which a color contour is used to show the normalized irradiation during the event (here assuming clear skies) with GDVs used to show the solar generation; a movie of the event with a one-minute resolution is available at [53].

III. Validation

Before presenting additional examples, it is important to address the issue of validation. From a modeling and simulation (M&S) perspective, validation is used to determine the degree to which the M&S accurately represents the real world from the perspective of the intended users. Here the users are assumed to be planners of large-scale electric grids, whose focus is (as noted earlier) to ensure future transmission system performance and corrective action plans to remedy identified deficiencies.

Given that planning is forward-looking, validation is focused on ensuring future ENIs are adequately modeled, and that the PFWs models adequately represent the impact of the ENIs on future grids. Except in rare situations like eclipses, future ENIs are not precisely known. Of course, historical information can be quite helpful in determining potential events to consider, as can M&S be applied to hypothesized ENIs. Still there is substantial uncertainty in the ENIs, so planners often need to consider a host of scenarios.

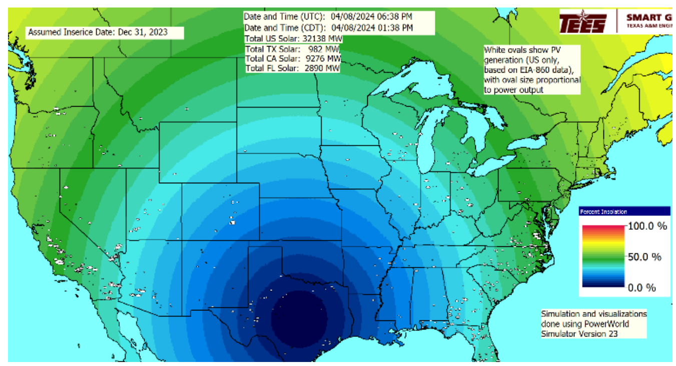

Figure 5: Impact of the April 8, 2024, Eclipse on US Solar Generation

From the perspective of this paper validation is focused on 1) determining the accuracy of PFW Models to represent the impact of the ENIs on the electric grid, and 2) ensuring the ENIs are being adequately represented at the location of the grid equipment. Out of scope here is the accuracy of the actual ENIs. So, for a wind generator validation here considers whether the PFW model adequately represents its wind power curve, and whether the wind speed source (e.g., ERA5 with its 0.25 degree resolution) adequately represents the wind speed across the wind farm. Not considered is the accuracy of the ERA5 data itself. Or for an earthquake the ENIs might be peak ground acceleration and then the PFW model implements an asset fragility such as used in [50].

The amount and type of validation will be ENI and PFW model dependent. In some cases, such as with wind generation, the PFW is fairly well defined, though temperature dependence might need to be considered [27]. However, there could still be errors because, as noted in [41], hub height wind speed over the wind farm can be quite localized, with variations well below the accuracy of many weather datasets such as ERA5 (a potential at least approximate correction for this is covered in the following example). For other ENIs, such as earthquakes and ice storms, there is currently a large amount of uncertainty associated with potential PFW models and/or the impact of the ENIs at the component location. As is the case with stability models, in which validation has been an ongoing effort for many decades, validation will be an ongoing activity, albeit hopefully with gradually improving models.

As an example of how validation can be used to improve the PFW models and their parameters, consider the common situation of determining wind generator maximum outputs based on wind data. Since wind generation is usually operated at maximum power, ideally validation would compare the generators' actual output with the calculated values. While actual output information might be available to power grid planners, it is seldom publicly available. However, some information is available, including 2017 individual plant capacity factors (CFs) [54]. This allows for comparison, which is done in Table 1 for ten large wind generators across the contiguous US (CONUS).

In the table Column 2 shows the actual reported value. Column 3 then shows the CFs from 2017 in [26], which uses the meteorological data described in [55] with 0.25 degree resolution. Column 6 then shows the calculated CFs using this paper's CF with ERA5 data (0.25 degree, 31 km resolution) and the WPCs from [26]. Here the Column 6 CFs are calculated by using the hourly weather for 2017, applying it at each generator's location using its WPC, summing the 8760 hourly values to get its estimated energy output for the year, and normalizing the result by dividing this sum by its power capacity times 8760 hours.

Table 1: Comparison of Actual vs Calculated Capacity Factors (CFs) (2017)

Plant Code	Name	State	Actual CF [54]	Ref [26] CF	This Paper CF	Wind Scalar
56290	Maple Ridge	NY	0.28	0.39	0.25	1.05
56777	Fowler Ridge	IN	0.25	0.28	0.25	1.0
57195	Lower Snake River	WA	0.24	0.21	0.15	1.22
57449	Blue Creek	OH	0.31	0.35	0.30	1.01
57501	Rolling Hills	IA	0.33	0.40	0.33	1.0
57787	Flat Ridge 2	KS	0.43	0.47	0.43	1.0
57983	Stephens Ranch	TX	0.41	0.50	0.51	0.88
58008	California Ridge	IL	0.44	0.44	0.38	1.09
58695	Grande Prairie	NE	0.44	0.43	0.42	1.02
58883	Highland	IA	0.39	0.45	0.39	1.0

Overall, the match is quite good. However, even if the WPC is correct an exact match would not be expected because of two opposite effects. First, since the actual CFs include the impact of some turbines not being available (e.g., on maintenance) and possible output curtailments due to transmission issues, the actual CF would be slightly lower than the calculated value. Second, given that with many weather datasets the wind speed would not be available at the wind farm, there will be the potential for error. Since wind farms are often built in locations with locally high winds (e.g., ridges or mountain passes), a weather measurement even just a few km distant would likely underestimate the wind speed. This is seen in the table data in which this paper's results tend to underestimate the actual CF.

One way in which the PFWs could be created to compensate for this difference is to include an additional "wind scalar" parameter, in which the calculated hub height speed is scaled to account for this terrain variation. While not a perfect solution, the improved results could be sufficient for transmission planning needs. The advantage of this "wind scalar" approach is the values need to only be calculated once, and then they can be used with all future studies. The calculated scalars for the table generators are given in its last column.

IV. Examples

This section provides three example applications of the paper's approach. The first shows the impact of including weather with the power flow. Wind and solar power generation units often function at their maximum capacities, based on the weather-dependent availability of the input wind or irradiation resources. Of course, over a large electric grid they would seldom all be at their maximum outputs. By directly modeling weather, planners can start with a realistic dispatch for these generators in the power flow, and then adjust other generators to meet constraints such as on area interchange. Outlier conditions could also be considered, such as times in which renewable generation is at its maximum or minimum. Figure 6 and 7 show and compare GDVs of all renewable generators larger than 20 MW in US at the times with high and low availability of renewable resources in the US based on EIA 860 grid data in the first quarter of 2024. For consistency with solar, only noon (US Central Time) was considered from 1940 to 2023.

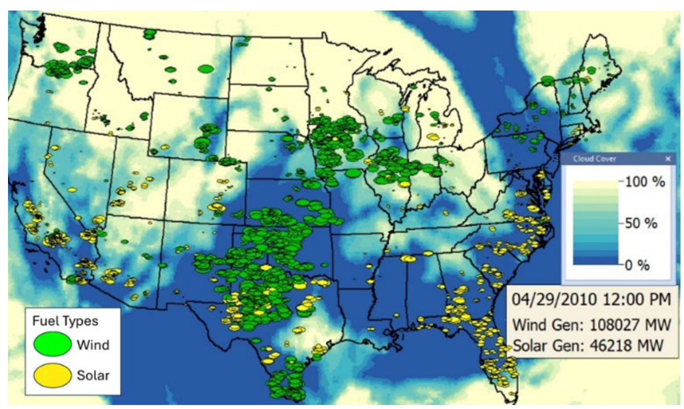

Figure 6: CONUS Wind and Solar at a Time of High Availability

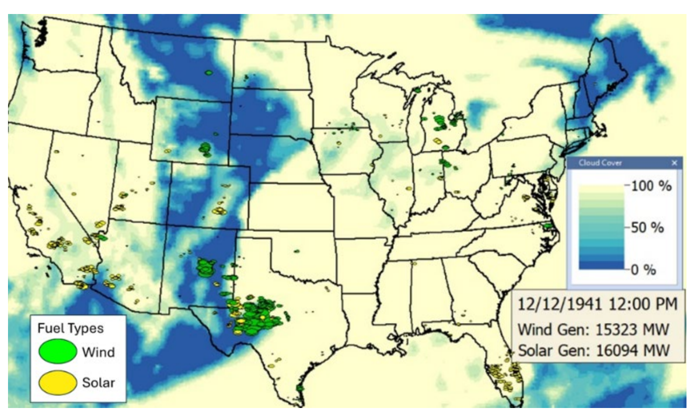

Figure 7: CONUS Wind and Solar at Time of Low Availability

On a percentage basis 73% percent of the available resources could have been producing under high conditions, while on 15% would have been available under low conditions. The contours show the cloud cover percentage with the blue color referring to 0% total clouds and symbolizing the blue-sky conditions, while yellowish white refers to 100% clouds. Figure 8 and Figure 9 duplicate this analysis except just focusing on wind generation for the previously mentioned 24K bus grid. In these figures the contour shows 100m wind speeds.

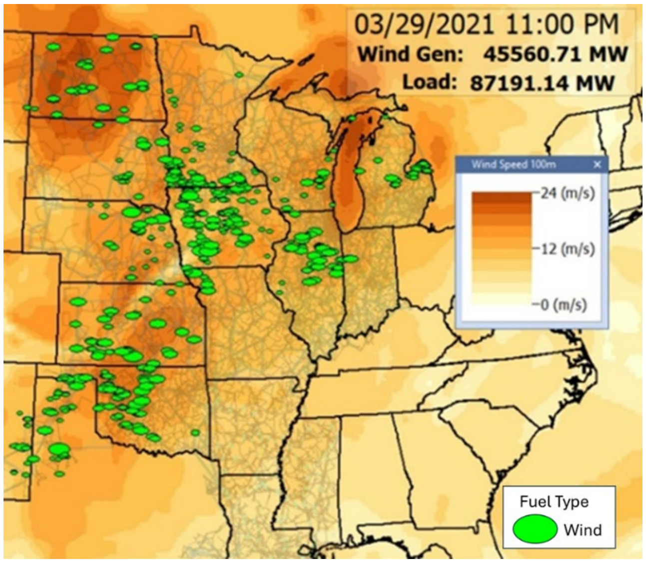

Figure 8: 24K Grid Wind Generation Output for Low Load, High Wind

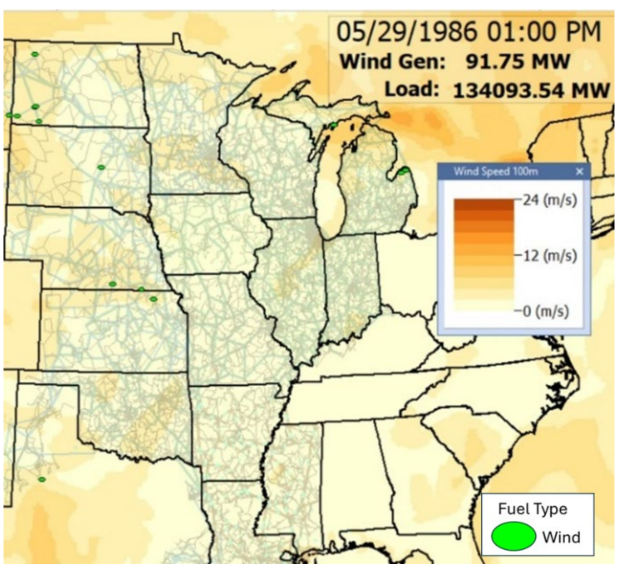

Figure 9: 24K Grid Wind Generation Output for Low Load, High Wind

The second example shows the impact of including weather on nodal electricity prices. Since renewable energy resources usually have zero or negative cost curves, the availability of these resources has a major impact on electricity prices and locational marginal prices (LMPs) [56]. Once PFW models have been setup for a grid, historical weather can be used to study how the grid would have responded, with a particular focus on more outlier conditions. The assumption with this type of analysis is future conditions could certainly be similar to what has occurred in the past. Using historical weather data of Texas (1940 to 2023), the two weather conditions that would have caused the highest and lowest renewable generation for the Texas 7K synthetic grid are found and an optimal power flow (OPF) with direct inclusion of weather measurements is solved under the same load for comparing the impact of these ENIs. Figure 10 shows data for the day and time with the highest values, and Figure 11 the one with the lowest. Both figures use GDVs to show the renewable generators larger than 10 MW with wind generation in green and solar in yellow while the sizes of the ovals are proportional to the available capacity of these units. Both figures also include a contour showing their bus LMPs [57].

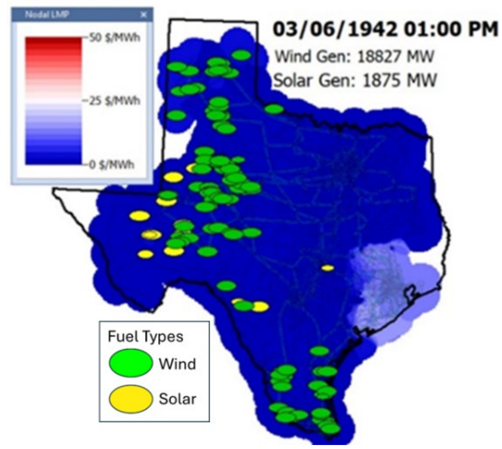

Figure 10: Time with the Largest Amount of Wind and Solar

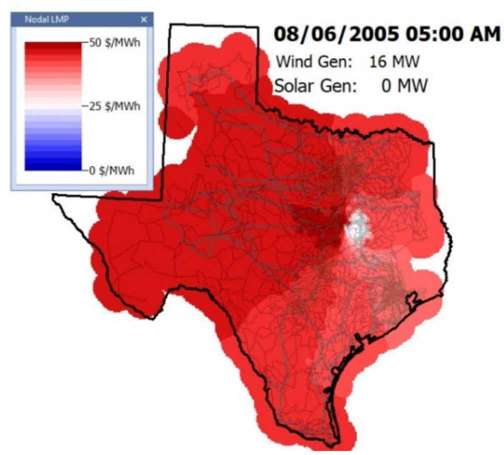

Figure 11: Time with the Least Amount of Wind and Solar

The last example considers times with weather conditions that would result in extended periods of low availability of renewable resources especially at times when the load is high. These events are defined as renewable resource droughts (RRD) [58], with a number of papers focused on their identification including a few covering North America [59], [60], [55]. To date RRD identification has been done by researchers; the goal here is to show how the approach presented here can help make it part of transmission planning.

What constitutes an RRD depends upon not just the weather conditions, but also on a number of other conditions. These include the available wind and solar plants, the load, the availability of other generation including hydro, and available transmission [55]. This information is often very system specific and would best be known by the transmission planners. So, the purpose of this example is to sketch out what a planner could do. In this example, to identify potential RRDs the ENI source is hourly weather data from 1940 to 2024, which is used to calculate the wind and solar generation output. Here it is based on the EIA-860 data for renewable generation units but could be generalized to an actual grid model. Specifically, the average generation output for each hour of each day across the entire dataset is calculated. This process involved aggregating hourly data for each day of the year and then averaging these values for each hour of a year over the 84-year period, resulting a graph that is shown in Figure 12. Renewable resource droughts in this work are identified according to the criteria outlined in [60], however these could easily be modified based on grid requirements. This figure provides a summary of the overall historical wind generation statistics at each hour over the years, displaying the average, minimum, and maximum, of historical data for each hour in Texas and shows drought threshold in dotted black curve.

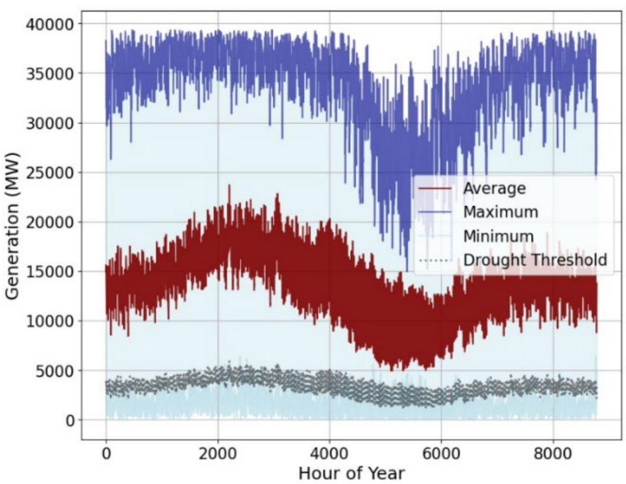

Figure 12: Historical Distribution of Wind Energy Assuming EIA-860 Units

Therefore, the first step to analyzing the renewable energy status is to analyze the available historical renewable energy outputs based on weather data at each point in time (here hour) and each zone under study. A starting point for drought zones is using states or provinces, or electric grid control areas but the RRD zones can be extended based on the impacted area under droughts at each time. So, graphs like Figure 12 should be created for each state or zone. After drought threshold is determined based on historical data statistics such as a specific percentage of average wind or solar generation at each hour of the year over all historical renewable power calculations, each point in the past, current or future is compared to the drought threshold. RRDs with long durations and large impacted areas can create serious problems for the grid. Also, the severity of the drought is based on the difference between the renewable output at the time of study and the defined drought threshold.

This strategy helps simulate possible RRDs in the future to find their impact on the grid. After the problems such as generation shortage, line congestion or voltage and frequency issues are identified, preventive planning actions such as building new transmission lines, proposing new resources especially energy storage devices and adding reactive control devices such as switching shunts are considered.

V. Conclusion and Future Directions

This paper has presented an improved approach for modeling the impact of weather and other electric grid resiliency events (ENIs) in the power flow with a focus on large-scale electric grid planning. Addressed issues include a modeling approach to represent the impact of ENIs on various electric grid components, considerations in adequately modeling the ENIs over the electric grid footprint of interest, and validation considerations. Several large-scaler examples have been presented with consideration of the visualization of the results. There are many directions for future work including the development of many more PFW models, continuing work in validation, the sensitivity of the results to the models, determining the required detail and variables in the representation of the ENIs, application of machine learning techniques to search for outlier conditions to study, computational considerations in processing many different ENI scenarios, and potential convergence issues associated with the power flow.

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