REGROW: Renewable Energy Generation Risk from Outlier Weather

Project Description and Technical Work Plan

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February 7, 2024

1 Background

A common rule-of-thumb in the solar industry is that the variability of a fleet of solar photovoltaic (PV) generators reduces by $\frac{1}{\sqrt{N}}$, where N is the number of PV generators in the fleet [1, 2, 3]. The fundamental assumption in these studies is that the dispersion of generators over a large area results in *spatial averaging* of local weather conditions, resulting in a bulk fleet behavior that is thought to be a "low-pass filter" of the power production from a single system. In short, the common assumption is that a collection of solar generators results in less variable, more stable fleet behavior.

This assumption holds well during "normal" weather and operating conditions, *i.e.*, conditions that are well described by historical data. However, during abnormal and extreme conditions, portfolios of PV generators (and other stochastic resources, *e.g.*, wind turbines) have been seen to exhibit *correlated losses*. The August 2020 heatwave in California provides an illustrative example. A confluence of factors has been identified in the joint report issued by California Independent System Operator (CAISO), California Public Utilities Commission (CPUC), and California Energy Commission (CEC) [4], but a critical contributing factor was region-wide under-performance of PV generators due to high temperature and reduced irradiance from wildfire smoke. We refer to this phenomenon of a collection of energy generators producing less power than expected as "correlated losses".

2 Project goal

Correct modeling of correlated losses under "abnormal" conditions (*i.e.*, conditions that are not well-described by historical averages) is critical for establishing distributed, renewable resources as a reliable energy source, especially as "abnormal" conditions become more common with the impacts of climate change [5]. Similar to how quantitative financial analysts must correctly model asymmetric and heavy-tailed multivariate distributions to mitigate correlated risk in investment portfolios [6, 7], we propose to study the phenomenon of correlated losses in collections of solar and wind generators (generator "fleets"). We will develop white-box, data-driven statistical models of fleet power production to support forecasting and management of grid resources under model predictive control schemes, making use of recently developed techniques for applying copula methods to energy resources with periodic probability distributions [8]. We will then incorporate the models into multi-forecast model predictive control simulations (see, *e.g.*, [9]). In short, we will demonstrate that robust forecasting and control (a) are possible under abnormal and extreme conditions and (b) provide the reliability required to manage correlated losses under increasing penetration of PV and wind.

3 Proposed technology

We are proposing to develop statistical methods and software implementation for analyzing correlated losses in solar and wind generators under abnormal and extreme weather events. These terms have been used by different actors in a variety of ways; we use the following definitions. *Abnormal* weather events are those not well-described by the typical historical expected values, such as summer heatwaves with temperatures 10–20°F above typical or months-long reduction in insolation (energy per unit area from sunlight) due to atypical atmospheric conditions. *Extreme* weather events are those that cause damage to the generators themselves, such as hail damage to solar panels or wind damage to turbines. We will develop a reproducible methodology and software package for carrying out the analysis of correlated generate losses under abnormal and extreme conditions, and we will use the tool to analyze case studies of previous events (*e.g.* the 2020 California Heatwave).

An integral component of this research is the development of data sets covering abnormal and extreme weather conditions and their impacts on PV and wind generators. The project plans on leveraging existing work, started under the PV Fleets project at NREL, described in more detail in §5. We intend to follow the methodologies for combining and labeling data sets described there to expand the available data to inculde both PV and wind generation, as well as both extreme and abnormal weather. Expanding the available data to cover all these categories will be an important focus of the proposed work. In addition, the proposed probabilistic models are designed to enable computationally efficient conditioning on any subset of variables. This will allow us to design abnormal and extreme "scenarios" in terms of meteorological variables (*e.g.*, ambient temperature and wind speed) and simulate the effects on fleets of PV and wind generators. We will be able to explore scenarios "more extreme" than those seen in historical data, but the authors note that the primary concern with climate change in the *increased frequency* of historicaly abnormal conditions [5].

Finally, we will simulate forecasting and control scenarios and demonstrate the efficacy of *multi-forecast* robust predictive control strategies for managing supply and demand on a grid with high penetration of solar and wind generators, under abnormal and extreme conditions. The development of advanced control methods along with rigorous simulation is intended to demonstrate an effective risk mitigation strategy for supporting grids with high renewable penetration.

4 Research pillars

Data set curation. We will curate data sets covering historical abnormal weather patterns (e.g. heatwaves) and extreme weather events (e.g. hurricanes). In particular, we will be looking to identify historical periods where wind and solar generators either produced less than is typical (abnormal weather) or were completely knocked offline (extreme weather). Collectively, we refer to these conditions as "outlier weather". In these time periods, we will be looking to obtain multidimensional data covering grid conditions, solar generation, wind generation, and meteorological conditions.

Risk modeling for renewable generators. We will develop risk models of renewable generator underperformance and outages. Our goal will be the ability to correctly model the likelihood of relatively rare events, including correctly capturing correlations between generators in an area and ambient meteorological conditions. The goal here is to be able to make a "nightmare scenario generator," i.e. a probabilistic model of poor performance and outages from collections of renewable generators.

Grid modeling. The focus of this pillar is to model real-world historical outage events, such as the 2020 heatwave and blackout event in California. We will create reduced-order sub-transmission and distribution models that capture relevant dynamics of outage events identified in Pillar 1. These models will provide the platform for developing and demonstrating the methods described in Pillar 4. To support this work, we will be enhancing SLAC's commercial release of Arras Energy software, formally known as GridLAB-D. This project proposes the extension of Arras Energy's distribution modeling capabilities to a new sub-transmission module, which will include all the necessary classes to model high-voltage transmission in sub-minutely timescales. The modeling tool will leverage the Grid Resilience and Intelligence Platform (GRIP), developed for the distribution system scale and extend the socio-economic resiliency metrics to high voltage use-cases.

Risk mitigation through robust control. We will explore methods for robust model predictive control that can interface with the risk models and grid models developed in Pillars 2 and 3. Our focus will be to develop methods that (a) handle probabilistic forecasts, (b) can gracefully balance multiple divergent forecasts (with different prior probabilities), and (c) is scalable to large problems (many assets, high time fidelity). We intend to focus our initial study and research on a previously published but not well-known method known as multi-forecast model predictive control (MFMPC).

5 Current state of the art

Tail risk modeling. Correlated risk has a long history of study the finance sector [10, 11, 6, 7] but has also resulted in some impressive failures [12]. Despite this, the industry has nonetheless been undergoing rapid growth in recent history [13], indicating certain successes in learning from said failures. (And from an applied mathematics perspective, few other domains have had such a compelling reason to tame high-dimensional, highly-non-Gaussian, time-dependent stochastic processes.) However, the details of modern financial risk models and trading algorithms are not typically public knowledge, as investment management companies consider these topics to be closely guarded intellectual property that give them market advantage. A rare and quite interesting exception that proves this rule is a 2000 paper in NeurIPS [14], which does not mention financial applications as all but is notably written by an employee of one of the more secretive investment companies. In our research, we have been recently exploring these topics at a fundamental level, trying to learn from both successes and failures and apply the general ideas to other domains. Recently, we published this paper at PVSC [8], which represents an early prototype of the type of methods discussed here. (NB, this work has begun under SETO Award Number 38529, but focuses more on modeling the "bulk" of the distribution rather than the tails.) The PVSC paper borrows from the copula work cited at the start of this paragraph and the "Gaussianizing flow" described in the NeurIPS paper, while maintaining a white-box, interpretable modeling framework. The REGROW project will be a natural extension and deepening investigation of this highly novel work. From our position working closely with Stephen Boyd [15, 16], we are uniquely prepared to draw on the lessons of quantitative finance when considering energy applications, while in no way being limited to a financial perspective. Briefly, other domains that have provided insight into the modeling of rare events include aerorospace [17], telecommunications [18], transportation systems [19], and nuclear power generation [20].

Data set curation. At the same time, important research is ongoing examining the impacts of extreme weather events on renewable generator performance [21]. In this recent paper, Jordan et al. compiled a valuable data set by merging fielded PV time series data from the NREL PV Fleets Initiative, and extreme weather event data from the Storm Events database, publicly available by the National Oceanic and Atmospheric Administration (NOAA). The authors built relationships between systems and extreme weather events by locating storms occurring within 10 km of a PV system, during periods where time series data was available. Each PV system was then manually assessed for storm impacts, with system outages (and length of system outage) recorded. Figure 1 shows an example PV system in the data set after a NOAA-recorded thunderstorm wind event, with a resulting system outage of approximately 6 days, reproduced with permission of the authors.

Grid modeling. This projects builds upon the modeling capabilities develop for Grid Resilience and Intelligence Platform (GRIP), originally a DOE GMLC (SETO & OE), as well as DOE CESER, TCF and DHS CAP S&T. GRIP provides the tools necessary to anticipate, absorb and recover from extreme events on near-term basis. The projects mainly focuses on granular analysis of the electrical distribution system prior to an extreme event and provides actionable insights to the electrical utility provider regarding the status of the system.

GRIP is deployed using GridLAB-D, which was originally developed by the US Department of Energy's Office of Electricity at Pacific Northwest National Laboratory to provide an agent-based simulation environment for evaluating the impact of emerging smart-grid technology on the performance of future power systems [22]. The simulation include modules for both steady-state and dynamic transient power flow analysis, advanced load modeling, renewable energy resources, weather, telecommunications infrastructure, and

Figure 1: Measured AC power time series from a PV Fleets system, where a thunderstorm wind event led to an outage (i.e. drop in AC power data) for approximately 6 days.

utility tariffs. The California Energy Commission funded SLAC National Accelerator Laboratory to extend GridLAB-D to support the requirements for integration capacity analysis, tariff design, deep electrification, and extreme-event resilience analysis, such as weather events and wildfires [23]. The main advantage of using GridLAB-D is that the simulation models do not presume normal system behavior. This is achieved by combining data-driven and physics-based models, which facilitates the study of extreme event scenarios by enabling resource, network, market, and consumer agents to respond to off-normal conditions that have not been previously observed. GridLAB-D has been commercialized by the Linux Foundation's LF Energy under the commercial name "Arras Energy" [24].

Robust control. Robust control has an extensive history, as evidenced by this 1987 review paper, summarizing the field up to that point [25]. We will be focusing our research on methods for robust *model predictive control* (MPC), of the flavor described in [9, §5.4]. The *multi-forecast model predictive control* (MF-MPC) problem is not at all new but can be thought of as a simple special case of more general methods for incorporating uncertainty and information patterns via multiple scenarios [26, 27, 28, 29, 30, 31, 32, 33, 34]. While such methods are clearly discussed in the control literature, the application of such methods is not wide-spread in the energy sector (or really any applied sector). Our focus in this project will be to interprete and building on this literature to develop a useful tool for planning and control and to make MF-MPC more accessible to energy applications.

6 Risks and mitigation

The primary risk to the proposed project is the availability of suitable large datasets, and the ability to share results publicly. By leveraging contacts with researchers already collecting the relevant data sets, we ensure access to suitable data to develop the proposed tools. A subset of the PV Fleets data will be used to support this project to ensure NDA compliance. Specifically, data sets used here will be covered under both SLAC and NREL NDA's, or are publicly available (NREL PVDAQ data sets). The initial outage data set compiled by Jordan et al. [21] will be leveraged and expanded upon during this research.

The NREL PV Fleets Initiative, which houses the PV Fleets data, is a US Department of Energy (DOE)-funded project focused on large-scale degradation analysis of fielded solar systems across the United States. The PV Fleets database contains over 3700 sites across the US, and over 56 billion rows of power, irradiance, and temperature time series data.

The NOAA Storm Events data set, which was used by Jordan et al. [21], contains reported severe weather events across the United States, including event type (floods, hail, tornadoes, hurricanes, etc), event start and end dates, beginning and end latitude-longitude coordinates, and additional information on event magnitude/severity if applicable. Data between 2008 to present will be used, representing over 800,000 extreme weather occurrences.

In addition to the PV Fleets and NOAA Storm Event databases, we intend to examine additional publicly available data sources for this work:

- The DOE-supplied Electric Disturbance Events dataset. This publicly available data set contains information on grid outages and disturbances across the US, and could be further correlated with PV or wind time series data to gain valuable insights.
- The NOAA climate data set, which contains information on heat waves in the United States. This data set, along with the NOAA Storm Event data set, will provide a comprehensive view of abnormal and severe storm events across the United States, to compare against fielded PV and wind time series data.

It is important to address previous data set curation from [21] to delineate new tasks for this work. The existing data set contains merged NOAA storm event data and measured PV data in the PV Fleets Initiative. System outage lengths due to storm events have been previously tabulated [21], so this new research will expand upon existing work by looking at production losses due to storms, including both outages and non-outage dips in system performance. Additionally, our new work will include additional systems added to the PV Fleets, PVDAQ, and PVOutput databases since the last extreme weather analysis was performed in January 2023. Furthermore, we plan to integrate grid outage data and climate data (heatwaves, cold snaps) with the Fleets and NOAA data sets, which has not yet been performed.

Finally, we are exploring contacts and are actively researching data sources for wind-focused performance and extreme weather data.

7 Impact

This project will prove via advanced modeling and simulation that abnormal and extreme weather events are not a barrier to large-scale renewable integration. One of the most common arguments for the ongoing need for fossil energy sources is to provide "grid resilliance" during extreme weather [35, §III-C]. We intend to disprove that notion by clearly demonstrating an approach for managing renewable generator risk that provides for reliable grid function through outlier weather patterns. Far from simply carrying out a case study or two, we intend to demonstrate the efficacy of our models and control frameworks both as a planning tool, able to explore what-if scenarios, and eventually as a real-time control tool for grid operators.

The methods being described here are, in general terms, inspired by approaches used successfully (and unsuccessfully) in quantitative finance to model and manage portfolio risk. Learning from these application and applying these approaches to the topic of renewable energy integration represents both an intellectual challenge—one that we are well-positioned to address—and an opportunity. We intend to perform rigorous, reproducible, open-source science that will thoroughly document these methods and establish them as usable tools for the energy sector. We see this as being deeply impactful for enabling high-penetration of renewables and achieving our goals for decarbonizing the grid.

8 Tasks and subtasks

1. Data Set Curation
   (a) Join the NOAA extreme weather data set, the NREL PV Fleet Performance Data Initiative data set, and grid outage data publicly available from the DOE to identify periods where PV systems experienced an outage or underproduction from abnormal or extreme weather events, and identify correlated grid outages. Each storm instance occurring within a certain radius (for example, 10 km) of a PV system will contain the following information:
      i. The type of storm event (wind, hail, hurricane), as well as any additional information on storm severity provided by NOAA
      ii. Whether or not the storm caused a system outage (ie loss of communications)
      iii. Whether or not the storm caused a grid outage (as determined by the grid outage data set)

iv. Length of grid outage, if applicable
v. Length of system outage, if applicable
vi. System metadata, including size, technology, and latitude-longitude coordinates
vii. The percentage production hit occurring within the 24- to 48-hour period of the storm occurring, when compared to previous production

(b) Perform the same steps outlined in subtask 1.1 with wind data

(c) Perform analysis and visualization of data sets curated and labeled in subtasks 1.1 and 1.2

i. Identify case studies of renewable generator underproduction which impacted grid stability
ii. Perform statistical analysis of PV and wind generator underperformance and outages, with respect to factors such as storm type and severity (hail, wind, hurricane, etc), geographic region/climate type, grid effects, and installation technology type
iii. Build out a dynamic visualization of case studies, utilizing The Cave VR visualization facility at NREL[1]

(d) Use the case studies identified in subtask 1.3.1 to isolate high-fidelity grid data for grid modeling activities. An example data source could include the ICA map from PG&E

2. Renewable generator risk modeling

(a) Research risk models used throughout various industries—finance, insurance, etc

i. Literature review
ii. Outreach to Stephen's connections at Stanford (e.g. Mykel J. Kochenderfer[2] and Dimitry Gorinevsky[3])

(b) Develop prototype correlated risk models
(c) Benchmark models on data from subtask 1.1 and 1.2 and downselect
(d) plement model in open-source Python code
(e) Fit open-source model to data from subtask 1.1 and 1.2 to publish fit model

3. Grid modeling

(a) Develop minimal sub-transmission module
(b) Develop power flow models of relevant grid dynamics in abnormal/extreme case studies identified in task 1
(c) Generate metrics for baseline analysis
(d) Coordinate with subtask 4.3 to implement control methods in grid simulator

4. Multi-forecast model predictive control for energy systems

(a) Research methods for multi-scenario model-base optimal control, appropriate for managing energy grids over multi-day periods

i. Must handle distributional forecasts of inputs to energy system
ii. Must handle high-impact, low-probability events

(b) Prototype and test control methods with data and models from tasks 1–3
(c) Coordinate with subtask 3.3 to implement control methods in grid simulator

5. Outreach and dissemination

(a) Form Technical Advisory Committee
(b) Workshop/industry engagement events

[1] https://www.nrel.gov/computational-science/visualization-analysis-data.html
[2] https://scholar.google.com/citations?hl=en&user=cAy9G6oAAAAJ
[3] https://scholar.google.com/citations?hl=en&user=l3v-53EAAAAJ

9 Milestones

Quarter	*Subtask*	*Description*	*Criteria*
1	1a	Complete solar data curation	Generate a tabular master data set with fused PV power, grid outage, and extreme weather data. For each entry in the data set, include the weather event and associated information (damage, severity, length, location), system information (power output following the event, system location and operating dates), and grid outage information (outage occurring, length if applicable).
1	2a	Complete risk literature review	Write first draft of "related work" section appropriate for a paper on risk modeling for renewable generators, with bibliography containing at least 10 sources and a synthesis/summary of relevant research. Hold initial meetings with Stanford professors studying risk and incorporate their input in draft.
1	5a	Industry outreach and technical advisory committee formation	Confirm inclusion of 6 or more outside organizations to sit on TAC
2	2	Complete wind data curation	Generate master data set in the same format as the fused solar data set described in subtask 1.1. Merge the solar data and the wind data and isolate 1-3 specific storm events for future investigation for grid modeling work. Storm events will be identified based on the number of PV and/or wind systems affected, presence of grid outages, and availability of high-resolution grid data.
2	2b	Create initial prototype risk models for PV generators	Implement at least 2 prototype models in Python and fit to curated PV system data with prelabeled performance outliers. Models must be able to generate estimates of the likelihood of low-probability events in the training data.
3	2b	Create initial prototype risk models for wind generators	Implement at least 2 prototype models in Python and fit to curated wind system data with prelabeled performance outliers. Models must be able to generate estimates of the likelihood of low-probability events in the training data.
4	2c	Complete benchmarking of prototype models and downselect	Identify single model to continue developing by comparing accuracy and computational complexity on test data sets

4	3a	Sub-transmission module code published in arras-energy/gridlabd	Source code with self-diagnosing autotests for new sub-transmission features passing with 100% on standardized minimal models
4	4a	Complete robust control literature review	Complete draft of 'prior work' section on a paper on robust control for renewable energy risk management. Must include no less than 12 sources.
5	2d	Release v0.1 of risk model fitting software	Installable as a python package and includes working example notebook(s)
5	3b	Subtransmission models for at least 1 use-case (e.g. extreme heat, high winds)	GLM files that pass validation with 100% based on source code in 3a.
5	3c	Baseline metrics for at least 1 use-case	Tabulated list of metrics for the use-case validated against actual event.
5	4b	Develop initial control prototypes and test on prototype risk models	Implement at least 1 prototype robust control methodology in Python and simulate at least 1 underperformance scenario to demonstrate proof of concept
6	1(c)ii	Publish paper/technical report on statistical analysis of curated data	Publicly release a paper via a conference or journal focused on analyzing the curated solar and wind data, focusing on storm-related underperformance/outages with respect to factors such as geographic region, storm severity, and installation type, among others.
6	2e	Publish fit risk models of PV and wind generator	Host model parameters along with documentation on public-facing website.
6	4b	Complete code implementation of control strategy and perform initial simulations	Control methodology implemented in installable Python package.
7	3d/4c	Complete grid simulations incorporating risk models and robust control	Tabulated and validated result outlining level of risk reduction against baseline scenario.
8	1(c)iii	Deploy interactive visualization in *The Cave* facility at NREL	Demo-able visualization available in The Cave VR facility. This demo will include the 1–3 cases isolated for grid modelling work, and examine all of the associated data for these cases simultaneously (production data, grid outage data, weather data, etc) for further insights.
8	5b	Hold workshop at NREL with stakeholders	Participant questionnaire

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