Proceedings of the 2023 Winter Simulation Conference
C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.

STOCHASTIC CLIMATE SIMULATION FOR POWER GRID NET DEMAND RISK ASSESSMENT

Rob Cirincione

Sunairio, Inc
509 S. Exeter St.
Suite 500
Baltimore, MD 21202, USA

ABSTRACT

Power grid planners and power portfolio managers are increasingly concerned with anticipating "net demand" risks, which is defined as customer demand minus renewables for a particular time period. Net demand is a better predictor of grid stress than peak demand in a grid with significant renewables penetration. For Holy Cross Energy, Sunairio simulated 1,000 probabilistic outcomes of hourly weather across a geographic region that encompassed the locations of customers and renewable energy resources (wind, solar), for 15 years. The hourly weather simulations were transformed to hourly energy simulations of customer demand, wind generation, and solar generation via machine learning models, creating a broad, climate-change-aware, coincident data set from which to quantify concurrent risks to net demand. Net demand paths of particular interest for grid planning were curated via statistical processing.

1 CUSTOMER PROFILE: HOLY CROSS ENERGY

Holy Cross Energy (HCE) is a Colorado-based rural electric cooperative (a rural utility that is owned by its members) which has a net zero mandate: they have a goal of providing 100% green energy to their customers by 2030. As a consequence, HCE is actively adding utility-scale wind and solar resources to its portfolio. This means that HCE manages an increasingly variable energy position that combines residential demand, commercial demand, solar generation, and wind generation.

Furthermore, the greatest portfolio risk for HCE, as an electric cooperative, is no longer anticipating and managing *peak* demand–but rather anticipating and managing *net* demand (demand minus renewables). Net demand poses a risk at both high levels (when HCE must be confident it can procure enough firm supply to cover its customer obligations) and low levels (e.g., when renewable generation exceeds demand and HCE may be forced to sell excess power at a loss).

Holy Cross Energy engaged Sunairio to quantify its hourly net demand risk over a 15-year planning period and create realistic demand-wind-solar scenarios that represent both typical and extreme system outcomes.

2 BACKGROUND

The weather conditions that drive generation shortfalls in a power grid which relies on renewables are concurrent events; e.g., a combination of high temperature, low wind speed, and high cloud cover. In fact, the "net demand" concept has replaced "peak demand" as a more relevant indicator of grid stress. If net demand is greater than available controllable generation capacity then a generation shortfall exists, resulting in brownouts or blackouts. Renewable generation surpluses may also be problematic, as described previously.

Power grid planners have traditionally relied on a mix of historical weather data and custom weather model simulations to produce a set of weather scenarios to evaluate net demand/generation shortfall risk–often over a multi-decade planning horizon. These methods suffer from three basic flaws: limited historical data sample sizes, an inability to incorporate climate change trends, and computational expense to generate new modeled data.

With respect to the first flaw (limited sample)–concurrent historical weather data are rarely available for more than 30 years, limiting the effective weather sample size to 30 because weather patterns occur in annual cycles. Climate change presents a further challenge to the use of historical time series data: if probability distributions are to be inferred from the historical weather series the data must be stationary, yet climate-change-induced trends are increasingly rendering that assumption invalid. The third drawback of current approaches mentioned above—the computational expense of generating new modeled data—relates to conventional, physics-based climate modeling that can require weeks or months of processing time to generate one simulation of local multi-year weather.

Sunairio addresses these shortcomings by using computationally efficient stochastic simulation techniques to replicate realistic correlated hourly weather patterns in high dimensions over grid planning time horizons. The resulting data set is much broader and representative of future weather risk than current alternatives, facilitating better net demand risk assessments.

3 DATA AND CLIMATE SIMULATION OVERVIEW

All climate models learn from historical data. Sunairio has built a proprietary archive of downscaled historical climate data using a combination of gridded climate reanalysis (estimates of historical global weather on a regular grid), satellite data, high resolution numerical weather models, and high resolution terrain data. The resulting data set allows Sunairio and Sunairio's customers to obtain hourly time series of hyperlocal historical weather at any location in the continental U.S., for heights above ground from 2m to 300m.

Before simulating future weather, empirical hourly probability distributions (8,760 per year) are estimated for every target location and every target weather variable. These empirical distributions are estimated on *detrended* historical data, which have been adjusted to remove long-term climate change trends.

The Sunairio climate simulation algorithm is inspired by a copula framework in which marginal probability distributions are derived from empirical hourly weather distributions on detrended data. Future years are simulated by adjusting the marginals in proportion to the measured climate change trends.

4 NET DEMAND SIMULATION FOR HOLY CROSS ENERGY

Sunairio simulated 1,000 paths (for 15 years) of hourly temperature, wind-turbine-hub height wind speed, and irradiance at locations corresponding to population centers, utility-scale wind farms, and utility-scale solar farms that were either in the HCE service territory or were resources contracted to HCE. Each weather path was then transformed to an energy simulation path by applying machine learning models for load (as a function of temperature), wind generation (as a function of wind speed), and solar generation (as a function of irradiance and temperature). High fidelity probability distributions of net demand over arbitrary time periods can be calculated easily with this data.

Sunairio also curated several paths for additional analysis based on HCE's guidance including a "typical" path (selected on median annual net demand), and "extreme summer risks", which are paths that have 99th percentile 8-hour net demand *and* regional temperatures greater than 90 degrees F.