Assessing Power System and Market Volatility During Heat Waves Using Probabilistic AI Forecasts: Insights from the WECC Region

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***Abstract*—The increasing frequency of extreme weather events, coupled with the rising penetration of renewable generation, poses significant challenges to forecasting system load, renewable output, electricity prices, and managing operational risk for system operators and market participants. This paper presents an integrated framework that combines machine learning–based probabilistic weather forecasts with load and renewable generation models, alongside a high-resolution electricity market simulator, to produce day-ahead forecasts of system conditions in a computationally efficient manner. A case study on the 14,606-bus WECC system during a heat wave demonstrates substantial deviations across ensemble members, including peak temperature variability of $\pm 6^{\circ}F$, wind generation differences of up to 4GW, load fluctuations of up to 3GW, and electricity price deviations exceeding 70%. These results underscore the magnitude of uncertainty in power system operations under extreme weather conditions and highlight the value of the proposed framework in supporting more robust, risk-aware decision-making.**

***Index Terms*—Extreme weather event, heat wave, machine learning, power system, probabilistic forecast.**

I. Introduction

The accelerating impacts of extreme events are reshaping the operational and planning landscape of modern power grids. A more volatile weather system, coupled with increasingly unpredictable electricity demand, presents new challenges for maintaining grid reliability and efficiency [1]. At the same time, the global energy transition has introduced a growing reliance on weather-dependent renewable energy sources, such as solar and wind, which are inherently challenging to forecast with high accuracy [2], [3]. The uncertainty surrounding weather patterns amplifies unpredictability on both the supply and demand sides of the electricity system heightening the risk of operational stress, price volatility, and large-scale system disruptions. Moreover, it adds complexity for market participants managing portfolios of generation assets, load obligations, and financial contracts, complicating decision-making and risk management in the electricity market. There is an increasing need for computationally efficient methods to generate probabilistic forecasts of coincident weather, load, renewable generation, and electricity prices in order to support system operators and market participants during extreme weather events.

A large body of research has been dedicated to producing probabilistic load and renewable generation forecasts [4] in the power systems domain. In general the probabilistic forecasts algorithms consists of two stages. The first stage involves producing point or ensemble forecasts [5] of meteorological variables by using numerical weather prediction (NWP) models [6] or statistical methods [7]. The second stage feeds the forecasts of the meteorological variables into parametric or nonparametric [8] methods to produce probabilistic load and renewable generation forecasts. Most of the existing literature focuses on the second stage by deriving probabilistic load and renewable generation forecasts given ensemble weather forecasts from NWP models using quantile regression [9] and its derivatives, bootstrap [10], Dirichlet process mixture model (DPMM) [8], and deep neural networks [11].

Despite their critical role in load and renewable generation forecasting, the initial stage of generating probabilistic weather forecasts—particularly for temperature, humidity, wind speed, and solar irradiance—has received comparatively limited attention in the power system field. The classical approach relies on ensemble weather forecasting [12], which uses NWP models based on the solution of large-scale partial differential equations representing the transitions between discretized grids of atmospheric states. While effective, NWP is computationally intensive, making it costly and time-consuming to produce a large ensemble of forecasts. In recent years, however, advanced machine learning techniques—such as 3D neural networks [13], graph neural networks [14], and Fourier neural operators [15]—have emerged as promising alternatives. These models offer improved short-term forecast accuracy while significantly reducing computational overhead.

This paper addresses a critical gap by developing an integrated framework that combines machine learning–based probabilistic weather forecasting, probabilistic load and renewable energy forecasting models, and an electricity market simulation engine to produce high-resolution, short-term forecasts of load, renewable output, and electricity prices in a computationally efficient manner. The resulting forecasts exhibit realistic, high-fidelity spatio-temporal patterns, offering valuable insights for system operators to enhance grid reliability and for market participants to better manage financial risk. To demonstrate the practical applicability of the framework, we conduct a real-world case study of the Western Electricity Coordinating Council (WECC) system during an extreme heat wave event. This analysis captures the probabilistic envelope of weather conditions under realistic but stressed scenarios, revealing critical spatio-temporal dynamics in load, renewable generation, and market price behavior.

The remainder of the paper is organized as follows. Section II describes the technical methodology for generating probabilistic forecasts. Section III presents the numerical case study conducted on the WECC system. Section IV concludes the paper with a summary of findings.

II. Technical Methods

The overall framework of the proposed probabilistic weather, demand, renewable energy, and electricity price forecasts is developed by integrating both custom and pre-built machine learning and power system models. Fig. 1 shows a high-level overview of the information flow between modules.

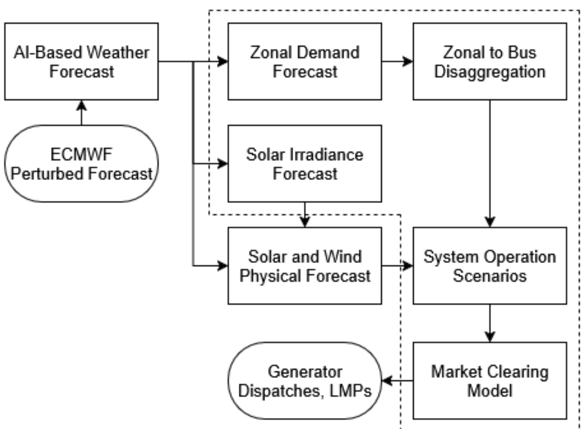

Fig. 1. High-level information flow of the proposed framework.

A. AI-based Short Term Weather Forecasting Model

This module leverages the pre-built Pangu-Weather model, a state-of-the-art medium-range weather forecasting model with 256 million parameters, trained on 43 years of hourly global weather data. Pangu-Weather produces forecasts at fixed time intervals down to one hour and with a spatial resolution of $0.25° \times 0.25°$, making it well-suited for the objectives of this study. This model is selected for its superior accuracy over traditional NWP methods and other AI-based approaches, particularly during extreme weather events [13]. Its performance advantage stems primarily from two key innovations: a 3D Earth-specific Transformer architecture and a hierarchical temporal aggregation strategy, which involves training a sequence of models for progressively longer lead times (1-hour, 3-hour, 6-hour, and 24-hour forecasts).

The input data to Pangu-Weather consists of a single hour snapshot of global weather typically from the European Center for Medium-Range Weather Forecasting (ECMWF). A subset of variables from ECMWF datasets is used, namely temperature, wind speed, and humidity, and at a range of atmospheric location defined by atmospheric pressure. Pangu-Weather outputs include the same variable set as the input to the model on the same global grid but inferred one time step forward.

B. Solar Irradiance Estimation Model

For this work, accurate forecasting of solar output is necessary. To accomplish this, more variables are necessary since the solar irradiance parameters – global horizontal irradiance (GHI), direct normal irradiance (DNI), and diffuse horizontal irradiance (DHI) – are not forecast by Pangu-Weather. One approach to resolve this problem is to base a forecast on the clear-sky irradiance. This is easily calculated using the pvlib Python package [16] given location and time of day. However, this method only finds a theoretical natural maximum and fails to account for atmospheric conditions that may decrease solar irradiance such as cloud cover. To account for atmospheric conditions, the variables forecast by Pangu-Weather can be used to forecast the difference between the clear-sky irradiance and the measured irradiance.

To accomplish this, an eight layer feedforward neural network with ReLU activation was trained to accurately forecast the solar irradiance parameters at any given location. This model takes in previous day and hours' weather and solar irradiance, future weather forecast information, latitude, longitude, sine-cosine time encoding, and clear-sky irradiance information. Training data was sourced from the ECMWF ERA5 dataset which includes the solar irradiance parameters surface short-wave radiation downwards (SSRD) and surface direct short-wave radiation (FDIR) [17]. These variables are directly related to GHI, DHI, and DNI. Once trained, this model performs at less than 5% mean absolute percent error (MAPE) on unseen testing data. Since there is a known relationship between GHI, DNI, and DHI, only two of the parameters need to be estimated to have a full understanding of the irradiance. This relationship is given by $\text{GHI} = \text{DNI} \times \cos(\theta_z) + \text{DHI}$, where θ_z is the solar zenith angle.

C. Renewable Energy Performance Simulator

To accurately simulate the performance of renewable energy sources, physics-based models representing solar and wind power plants are employed to compute their respective power outputs. The ADR solar cell model [18] with the default panel parameters from pvlib is used to produce power outputs of solar farms. The windpowerlib Python package [19] is used to estimate the power output of wind farms by interpolating along standardized wind speed-based power curves generalized for various common turbine types. Together with the solar model, these tools are employed to estimate the maximum potential power output of renewable energy resources at any given hour.

Estimating renewable energy outputs from forecast weather data requires knowledge of the geographic locations of generation assets. However, the network model used in this study does not include geo-coordinates for individual generators. To overcome this limitation, a representative subset of solar and wind generators was selected to approximate the spatial distribution of the broader renewable fleet. The geographic locations of these generators were identified using publicly available data sources such as the EPA's eGRID dataset. This subset represents over 30% of the total installed renewable generation capacity in the system. The average hourly capacity factor of the identified generators is then used as a proxy to estimate the output of the remaining, unlocated generators.

D. Demand Forecasting Model

To model the complex relationship between weather variables and electric load, we trained a convolutional neural network (CNN) that captures spatio-temporal dependencies between gridded weather data and zonal electricity demand. CNNs are well-suited for this task because they can extract local and hierarchical features from structured spatial data, enabling the model to represent complex, nonlinear relationships across weather fields that are difficult to model explicitly using traditional techniques. This model inputs a $121 \times 121 \times 384$ tensor representing gridded weather variables inferred by Pangu-Weather. The inferences are bounded by 25° N - 55° N latitude and 100° W - 130° W longitude. This tensor includes historical and forecast weather over a 48-hour window, or the past and future inferred 24 hours.

The CNN architecture consists of four convolutional blocks, each block comprised of two convolutional layers with kernel size 3 and stride and padding of 1, followed by 2×2 max pooling. The outputs of the convolutional blocks are then passed to a five-layer fully connected head with ReLU activation. At the start of this set of dense layers, non-spatial features such as the previous 24 hours' zonal demand and sinusoidal temporal encoding are concatenated. These encodings allow the model to be agnostic to a starting time so it can forecast 24-hour ahead from any point in the daily cycle.

The model outputs a full 24-hour day-ahead demand forecast for the load areas represented by the CAISO region. Once trained, this model performs at under 5% MAPE for all load areas on unseen testing data for a full 24-hour cycles.

E. Market Clearing Module

The probabilistic weather-informed demand and renewable generation potential forecasts are fed into the market clearing module, which includes two models: unit commitment (UC) and economic dispatch (ED). The UC and ED problem formulations follow [20] and [21] to minimize the system operation costs subject to a set of technical and system-level constraints such as nodal power balance, generator maximum and minimum limits, hourly ramp rate limits, and line flow limits. The outputs of the UC problem include the generator on/off schedules, which are fed into the ED problem. The outputs of the ED model includes the final generator dispatches and locational marginal prices (LMPs). The UC problem is implemented in YALMIP [22] and solved using Gurobi [23]. The ED problem is solved using MATPOWER's optimal power flow tools [24].

III. Numerical Study

A. Data Sources

The case study examines the heat wave that affected the western United States on September 5, 2024. On this day, a demand response event was triggered in the CAISO region, coinciding with elevated temperatures across the WECC area.

This work is built on historical hourly data from multiple sources, including the California Independent System Operator (CAISO)'s Open Access Same-Time Information System (OASIS) demand dataset [25], ECMWF's ERA5 reanalysis [17] and Meteorological Archival and Retrieval System (MARS) perturbed forecast weather datasets [26]. Additionally, a modified version of the WECC 2034 production cost model is employed to emulate system and market operations on September 5, 2024 [27].

For the machine learning modules trained on historical data, including the solar irradiance and demand forecasting models, the period from 2017 to 2023 was used ensure accuracy and relevance to the simulated operating conditions.

1) ECMWF: This study utilizes the ECMWF ERA5 reanalysis and the MARS Perturbed Forecast datasets to obtain high-resolution, physically consistent weather data. ERA5 is widely used for historical weather modeling due to its global coverage, high spatial and temporal resolution, and robust data assimilation framework. In our modeling framework, ERA5 data is employed to train zonal demand and solar irradiance forecasting models, incorporating meteorological variables such as surface and atmospheric temperatures, humidity, wind speed, and solar irradiance.

For forward simulations, we utilize the MARS perturbed forecast dataset. These ensemble forecasts enable the simulation of power system operations under a range of plausible weather scenarios, facilitating the construction of uncertainty envelopes for key system and market variables such as demand and locational marginal prices (LMPs). This ensemble-based approach captures the inherent probabilistic nature of weather forecasts and quantifies their downstream impacts on power system performance.

2) CAISO: The zonal demand forecasting model is trained using publicly available hourly demand data from CAISO OASIS, covering various load zones. As hourly historical zonal demand data for the full WECC region is not publicly available, we extrapolate CAISO-based forecasts to the 43-zone WECC model using inverse distance weighting (IDW) based on estimated population-weighted centroids. To maintain consistency with zonal demand magnitudes, each aggregated demand is normalized to the base load defined in the WECC model and then scaled accordingly. This method leverages spatial correlation in weather-sensitive demand patterns to approximate zonal load behavior beyond CAISO. While it introduces some simplifications, the approach offers a practical and scalable solution for integrating high-resolution forecasts into large-scale power grid simulations.

3) WECC: This study employs the WECC 2034 production cost model as the foundation for power system simulations. To better reflect operational conditions on September 5, 2024, and to reduce computational complexity, several model adjustments were made. First, the network was pruned to retain only buses with a base voltage of 69 kV or higher; demand from lower-voltage buses was aggregated to their corresponding high-voltage substations. Second, thermal line flow constraints were enforced only for transmission branches rated at or above 110 kV. Additionally, to maintain temporal consistency with the study date, only generators with commissioning dates prior to September 5, 2024, were considered operational and dispatchable. Following these modifications, the resulting system comprises 14,606 buses and 4,445 generators.

B. Numerical Results

1) Probabilistic Forecasts for Weather: As shown in Fig. 2, peak temperatures across a substantial portion of the WECC region fall within the 90°F to 110°F range. Leveraging ensemble forecasting allows us to assess the spatial and temporal uncertainty of temperature throughout the region. While the majority of absolute temperature deviations across ensemble members remain within $\pm 3°F$, certain areas exhibit variations in peak temperatures of up to $\pm 6°F$ during periods of peak load, as illustrated in Fig. 3.

This AI-based method enables rapid ensemble forecasting. While NWP models may require several hours to generate 24-hour forecast trajectories, this method produces forecasts for each ensemble member in under 2 minutes, enabling computationally efficient generation of full ensemble trajectories.

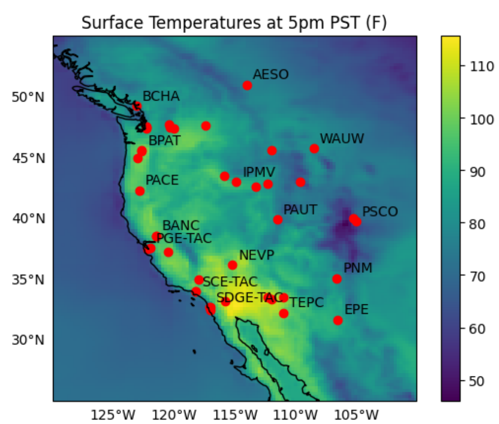

Fig. 2. Surface temperature at 5pm PST

2) Probabilistic Forecasts for Renewable Generation: Using ensemble weather forecasts, Fig. 4 highlights the variability and forecasting challenges associated with wind power. The figure shows the total wind generation potential across the WECC region over the course of the day for multiple ensemble members. A notable inverse relationship emerges between wind power availability and system load: ensemble

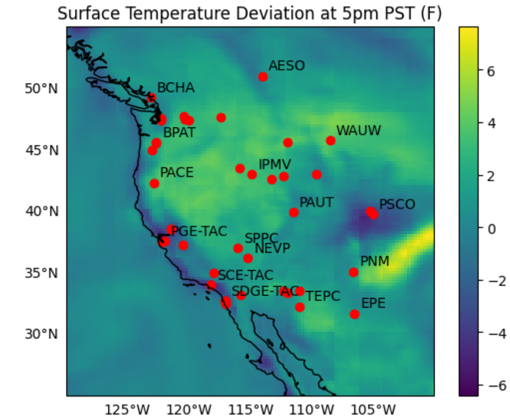

Fig. 3. Surface temperature deviation at 5pm PST

members with the lowest peak loads exhibit the highest peak wind generation potential, while those with higher demand show lower wind generation potential. This underscores the importance of incorporating weather-driven uncertainty into operational planning on heat wave days.

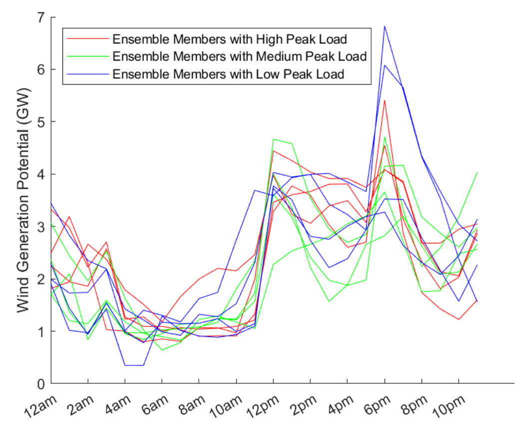

Fig. 4. Ensemble system level wind generation potential forecasts

3) Probabilistic Forecasts for Loads: Fig. 5 presents the 24-hour day-ahead WECC system load and net-load profiles across ensemble members. Solid lines represent the total system load, while dashed lines indicate the net load, defined as total load minus solar and wind generation. At the time of peak demand, the ensemble forecasts reveal a spread of nearly 3 GW in total system load, highlighting the significant uncertainty that system operators must account for in day-ahead operations on heat wave days.

4) Uncertainty in Load Area LMPs: Fig. 6 shows the percentage variation in LMPs relative to their ensemble means, disaggregated by load area. The results reveal substantial heterogeneity in LMP uncertainty. While some load areas exhibit relatively low variability—less than 20% in certain regions—others, such as the SPPC area, show significantly higher uncertainty, with average LMPs fluctuating by as much as 70% across ensemble members. This spatial disparity

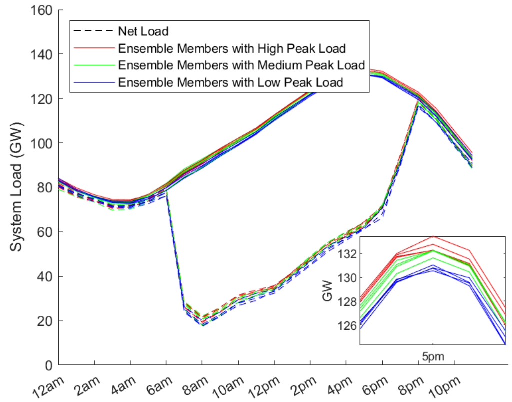

Fig. 5. Ensemble load and net load profiles on the heat wave day

underscores the importance of accounting for location-specific risk in market and system operations.

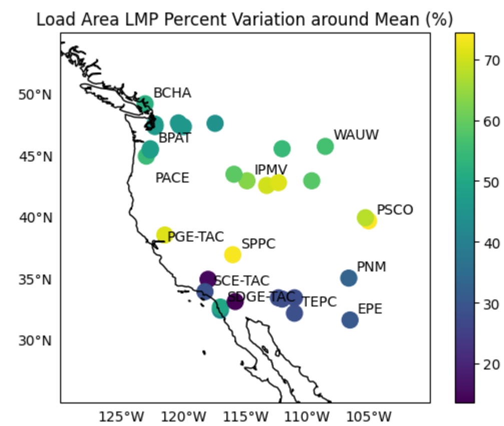

Fig. 6. Load area LMP % variation across ensemble members at 5PM PST

IV. Conclusion

This work presents a comprehensive framework for quantifying variability and uncertainty in power system load, renewable generation, and market prices under extreme weather conditions. By integrating AI-based ensemble weather forecasts with machine learning models for solar irradiance and zonal demand, as well as physics-based models for solar and wind generation, we capture the spatio-temporal uncertainty inherent to grid operations. Leveraging a modified WECC-scale transmission network coupled with a market-clearing model, we simulate system and market performance across ensemble members to assess the spatial distribution of LMP uncertainty. The results underscore the critical role of uncertainty-aware forecasting in supporting more resilient and informed power system operations during extreme events.

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