Power systems are managed through decisions made at every timescale: solar and wind generation must be predicted minutes ahead, operating reserves committed a day ahead, and generation and transmission investments planned decades ahead. The rapid growth of weather-dependent variable renewable energy (VRE), climate-driven weather variability, and demand growth from electrification and "large loads" are increasing uncertainty in both investment and operations across timescales. To quantify this uncertainty and improve these decisions, I develop computational methods that combine **probabilistic forecasting** and **remote sensing** with **stochastic models** for **electricity market operation** and **system planning**. As an electrical engineer trained in both power systems and artificial intelligence and machine learning (AI/ML), I have contributed at each timescale: minutes-ahead solar nowcasting using sky-imaging hardware, day-ahead forecasting of VRE generation and demand for reserve allocation, scenario-reduction strategies for stochastic unit commitment, and multi-decade capacity expansion planning for India, the world's third-largest electricity grid. This work has been published in *Nature Communications*, *Applied Energy*, and *Solar Energy*. As a faculty member, I will build a program that connects these timescales, develops open-source tools, and translates methods into practice for grid operators, policymakers, and market participants, so that sustainable electricity systems can be planned and operated reliably and affordably.

Planning Low-Carbon Power Systems

India is the world's most populous country and the fastest-growing major economy. With electricity demand projected to grow by 6.5% per year and approximately $450 billion expected to be invested in new electricity infrastructure over the coming decade[1], planning decisions made now will shape global emissions for a generation. I am the principal developer of *GridPath-India*, an open-source Python platform for long-term power system planning. The project is an international collaboration with Prof. Deshmukh at the Environmental Markets Lab (emLab) at UC Santa Barbara (UCSB), *Prayas Energy Group*, and *Sylvan Energy Analytics*, funded by the *World Resources Institute (WRI)*.

The platform integrates multi-period **capacity expansion** and **production cost** modeling, VRE resource assessment, bottom-up demand scenarios, and India-specific technology cost projections to identify least-cost, reliable, low-carbon investment pathways that are robust across a wide range of demand, cost, and resource futures (Fig. 1). The model and datasets are publicly accessible[2] (the manuscript is under review, and a *preprint* is available). I have supported hands-on training workshops in India built around illustrative models of three Indian states to transfer the platform and model to local analysts and institutions.

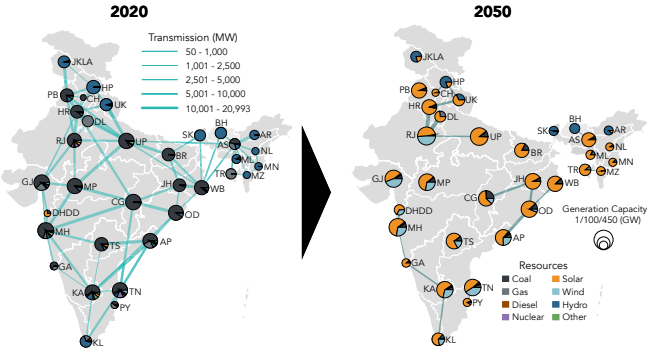


Fig. 1: *Least-cost low-carbon expansion of India's electricity system from GridPath-India: existing and new interstate transmission (line width and color) and generation by technology (circle size and color) in 2020 (left) and 2050 (right). Adapted from [2].*

This planning framework now anchors a growing research collaboration. I initiated a prospective *weather-synchronized* sequential Monte Carlo **resource adequacy** study (18 weather years×18 outage years) of India's electricity sector in 2040 and trained A. Sharma, a postdoctoral scholar, to use *GridPath-India*. Our analysis, now in final preparation, examines how weather-dependent generation, growing demand, policy goals, and extreme weather events increase the risk of unserved energy. I presented it as a poster at the *2026 Macro-Energy Systems (MES) Workshop* at Georgia Tech, and presented my system-level reserve allocation work at the same workshop at Princeton in 2024. I am working with graduate students S. Prasad and W. T. Wang at UCSB and S. Cherukumalli at Berkeley on coal retirement strategies that account for air pollution, employment, and land-use constraints. I am also leading a project on **capacity credit** methods[3] for estimating VRE contributions to planning reserve margins, in which I mentored an undergraduate student who presented preliminary results at the *SACNAS National Diversity in STEM Conference*.

Grid Operations under Uncertainty

The U.S. generated approximately 4,430 TWh of electricity at an average wholesale price of $48/MWh in 2025[4]—more than $200 billion in annual electricity market transactions—so even modest improvements in **unit commitment** and **economic dispatch** (UC/ED) decisions can yield billions of dollars in savings while reducing VRE curtailment and load shedding. The obstacle is computational. Researchers have studied stochastic formulations of the unit commitment problem since the 1990s[5], yet solving them over realistic networks with many scenarios remains intractable for day-ahead timelines[6].

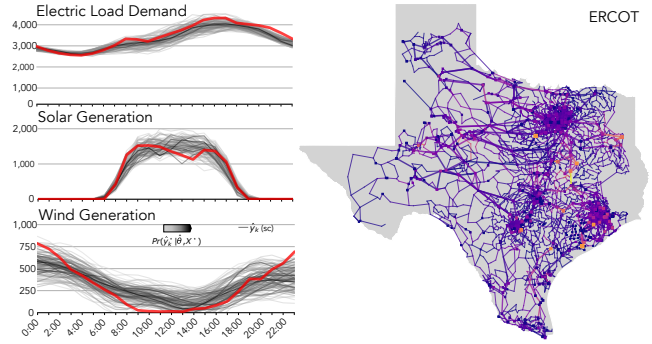


Fig. 2: *Day-ahead probabilistic scenarios for load, solar, and wind generation (left; grey = scenarios, red = realized) and the 7,000-bus ERCOT test network used in the Vatic Monte Carlo UC/ED simulator (right). Adapted from [7, 8].*

In collaboration with Prof. Ludkovski (Statistics and Applied Probability), the Department of Operations Research and Financial Engineering at Princeton University, and *Scoville Analytics*, with funding from the *Advanced Research Projects Agency–Energy (ARPA-E) PERFORM* program, I developed scenario-reduction strategies based on the statistical concepts of centrality and outlyingness and using depth measures from the **functional data analysis** literature. Our team developed *Vatic*, a Monte Carlo UC/ED simulator that extends Sandia's *Prescient* to the stochastic framework. We tested the approach in *Vatic* with the probabilistic day-ahead scenario generator *clnSim* on a realistic 7,000-bus ERCOT grid (Fig. 2). The reduced subset of joint load, solar, and wind scenarios captures most of the operational risk, from generation costs and reserve shortfalls to load shedding and curtailment, while sharply reducing the computational burden of stochastic optimization. We published this work in *Applied Energy*[8].

Energy Meteorology

In the U.S., solar capacity grew from 26 GW in 2015 to 272 GW in 2025, accounting for 52% (32.5 GW) of all new generation capacity last year alone[9]. As solar share grows, so does the operational cost of every forecasting error[10]. I began working on this problem during my Master's studies at the University of New Mexico (UNM), on a competitively awarded *UNM–Avangrid (Iberdrola) Foundation* graduate scholarship, where I developed unsupervised deep learning methods for feature selection in mesoscale meteorological data to improve hour-ahead solar forecasting[11].

My PhD research, advised by Prof. Martínez-Ramón and funded through the *National Science Foundation (NSF) EPSCoR* program, moved from forecasting with existing weather data to creating the observations themselves. Building on pioneering ground-based sky-imaging efforts[13], and working with Prof. Mammoli (Mechanical Engineering) and industry partners, I helped design and build two **sky-imaging** systems, *Ladybug*[14] and *Girasol*[15], which collect real-time far-infrared and high-dynamic-range visible imagery (Fig. 3). We published the resulting dataset, which has now been downloaded more than 1,300 times[16]. Using this hardware, I developed physics-informed computer vision and Bayesian learning methods for cloud detection, cloud tracking, and perspective geometric correction, and a forecast model that fuses information from multiple sensors. I published these advances in leading journals spanning renewable energy[17], machine learning[18], and remote sensing[19], as well as in a highly cited review on computer vision and deep learning for solar

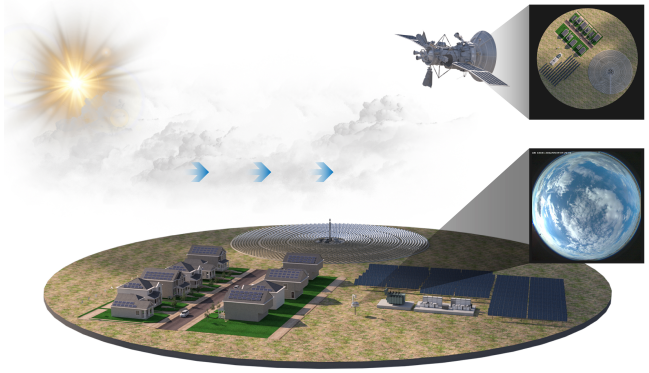


Fig. 3: *Ground-based sky imaging, satellite, and NWP data for intra-hour and day-ahead solar forecasts. Adapted from [12].*

forecasting[12].

At UCSB, I extended this forecasting work from single sites to entire systems. Probabilistic forecasts are widely recognized as essential for operating power systems with high VRE shares[20,21], yet system operators still rely largely on deterministic point forecasts. I developed a **probabilistic day-ahead forecast** that generates spatially and temporally correlated scenarios of electricity demand and wind and solar generation from numerical weather models, using multi-task Gaussian processes[7]. This work was supported by my *California NanoSystems Institute (CNSI) Climate Innovation Postdoctoral Fellowship* (2023—2025), a competitive award for research advancing California's climate goals, with additional funds from the Institute for Energy Efficiency (IEE) *Research Seed Program* and the CNSI *Climate Innovation Fund.* Applied to the three zones of the California Independent System Operator (CAISO), the best-performing model improves forecast skill by 25% relative to CAISO's own forecast, and we showed that forecasts based on joint probability distributions allocate operating reserves more effectively than deterministic approaches. This study was published in *Nature Communications*[7], the software is open source, and I presented it at the *MIT Energy Initiative* (2024) and at the ESIG *Forecasting & Markets Workshop* (2025). In ongoing work with Prof. Ludkovski, I am developing a probabilistic, nonparametric **rolling update** that revises VRE day-ahead uncertainty throughout the operating day (under review). A single adaptive, training-free model updates uncertainty minute by minute across every asset and node in the ERCOT grid model, sharpening predictive bands by 15–22% relative to the day-ahead forecast across significance levels.

Research Directions

These three lines of research converge on the same knowledge gap: the methods that quantify uncertainty and the decisions they are meant to inform remain disconnected. Forecasts are probabilistic, but reserves are still procured deterministically. Investments are optimized for least cost, yet reliability contributions are still valued with heuristics, even as those contributions become increasingly variable. As a faculty member, I will build a research group around three interconnected questions:

1. *How can AI/ML improve probabilistic forecasts of electricity demand, VRE generation, and prices as extreme weather events become more frequent?*
2. *How can weather and climate uncertainty be translated into planning and operational decisions?*
3. *How should markets value uncertain contributions to reliability so that affordable electricity and investment recovery hold together as energy systems decarbonize?*

In the near term, I will pursue three concrete projects that build directly on my current work. First, **dynamic reserve requirements**: extending my rolling update framework to set operating reserves in real time from probabilistic forecast revisions, replacing static reserve rules with uncertainty-aware procurement. Second, **capacity credits under climate non-stationarity**: building on my capacity credit and resource adequacy work to value the reliability contributions of wind, solar, and storage when historical weather is no longer a reliable guide to future extremes[22]. Third, **market mechanisms for uncertainty**: connecting both threads to pricing, asking how ancillary service and capacity markets should compensate generators when reliability contributions are probabilistic. Methodologically, these projects will advance scalable stochastic optimization, probabilistic modeling, and decision-making for low-carbon energy systems that are weather-dependent and vulnerable to climate change. Students will drive this agenda at every level: undergraduates will contribute through senior design projects and research internships in data acquisition, weather and power system data pipelines, and reliability-risk visualization, and graduate students will lead the forecasting, optimization, and market modeling research, contributing to publications, open-source code, and technical reports.

This agenda aligns with the *NSF Energy, Power, Control, and Learning (EPCL)* and *Algorithms for Modern Power Systems (AMPS)* programs and the *Department of Energy (DOE) Grid Modernization Initiative (GMI)*, and will form the core of my *NSF CAREER* proposal. I have contributed as an investigator to multiple funded research programs (NSF, ARPA-E, WRI), and these directions create natural opportunities for collaboration with NLR, LBNL, LLNL, and PNNL, as well as with industry partners in asset management, electricity markets, and grid reliability.

Over the longer term, my group will integrate localized weather variability and extreme events into power system planning and operations, which my remote sensing background makes feasible. As heat waves, droughts, wildfires, hurricanes, and Public Safety Power Shutoff (PSPS) events create growing reliability risks, the same skills I developed building imaging systems and processing their imagery apply directly to satellite imagery, weather reanalysis, and climate projections. My group will develop AI-based weather forecasting and decision-support models that anticipate evolving conditions such as wildfire propagation, smoke movement, flooding, and severe wind events, and translate these forecasts into infrastructure investment and operational decisions under climate risk. Undergraduate students will work with satellite imagery and wildfire smoke datasets, conduct geospatial analysis, and help validate numerical weather prediction and atmospheric transport models. Graduate students will lead experiments and model development in collaboration with atmospheric and computer scientists. This line aligns with the *NSF Cyber-Physical Systems (CPS)* and the *DOE Grid Resilience and Innovation Partnerships (GRIP)* programs.

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