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Supporting an Increasing Share of Renewable Energy

Forecasting and Market Design Advances

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ELECTRICITY SYSTEMS AROUND the world are decarbonizing, driven by reductions in the cost of renewable energy and encouraged by supportive regulatory policy. Electricity market designs are increasingly being tested to ensure that the bulk power system can deliver reliable, cost-effective energy to all consumers.

Underpinning the delivery of reliable, cost-effective energy requires several sequential processes ranging from short term (e.g., day-ahead energy scheduling and real-time power dispatch) to long term (e.g., making an investment decision to build a new generation or transmission asset). All of these processes are impacted by the accuracy of forecasting.

The bulk power system is transitioning from one where most of the generation came from conventional generating units to one where the predominant amount of generation comes from emission-free resources, such as wind and solar photovoltaic (PV) generation, which have low marginal costs due to

Digital Object Identifier 10.1109/MPE.2021.3104132
Date of current version: 18 October 2021

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zero fuel expenses. This change is increasing the commercial pressure on existing conventional power plants, potentially leading to their closure earlier than originally planned. As the share of the supply mix where the fuel source is weather dependent expands, the importance of accurate weather as well as wind and solar generation forecasting similarly grows.

Furthermore, the proliferation of distributed energy resources, such as behind-the-meter solar PVs, batteries, and electric vehicles, is providing opportunities for new market participants with innovative new business models, such as virtual power plants.

This confluence of factors is leading to a renewed focus on the optimal integration of forecasting and markets to ensure

- ✔ uncertainty and risk are prudently managed day to day
- ✔ essential system services are adequately procured and compensated for
- ✔ appropriate market signals exist to incentivize and achieve the necessary investment
- ✔ reliable energy is delivered cost-effectively.

The Evolution of Forecasting and Its Increasing Importance

Load-forecasting techniques have developed since the 1950s, and the field has a high level of maturity. It is already widely integrated into the operational procedures of system operators and market agents. However, existing load-forecasting methods require adjustments to tackle two new challenges:

- ✔ accounting for the influence of distributed generation, demand response programs, and extreme weather events in load profiles
- ✔ exploiting smart metering data in a hierarchical load-forecasting framework across multiple voltage/system levels.

For long-term horizons (years ahead), load forecasting is becoming highly dependent on technology adoption, such as the proliferation of PVs, electric vehicles, and smart appliances. This means research in technology forecasting should be revisited to improve forecast skills.

Figure 1 depicts the model and value chain for renewable energy forecasting. As a first step, numerical weather prediction (NWP) models generate forecasts of weather variables for horizons up to several days ahead, usually with updates every 6 h. Spatial resolution can go down to 1 km and temporal resolution to 1–3 h. For very short horizons (several minutes to a few hours), forecasts of the weather variables can be generated from satellite- or sky imager-based models.

These forecasts, together with measurements from renewable energy source (RES) plants, are then used as inputs to dedicated RES forecasting models to predict the power output of these plants. If the horizon is very short (typically up to 2 h), forecasts can be based only on onsite measurements as well as satellite and sky imager data.

The last step is a decision-aid phase, which can be either a human expert who visualizes the forecast products and makes a choice or an automated software tool that involves some optimization functions. This value chain presents several gaps and bottlenecks at different levels, which are also shown in Figure 1.

The use of forecasts and market clearing (and, more generally, decision making) are inextricably linked across the majority of electricity markets around the globe. What may differ is how they are integrated, who is responsible for providing them, and what type of forecast is needed at which operation stage.

Accurate long-term load and renewable energy forecasts are necessary, not just for prospective renewable generation investors to know their potential for revenue to justify builds but, increasingly, for all other prospective technologies. These forecasts can help investors and system planners understand the need for all technologies to support resource adequacy. They also provide insights on prices that may impact the profitability of each technology in different ways.

Regions in the United States and Europe typically have day-ahead markets, which allow for price certainty in determining the efficient unit commitment of resources through either centralized or decentralized unit commitment procedures. Day-ahead load, wind, and solar forecasts are crucial for these markets and have been the domain of specialized forecast providers worldwide. These forecasts may be provided by the market participants or system operator to ensure reliability through subsequent processes, such as the reliability unit commitment that follows the day-ahead market in the United States.

Despite their name, real-time markets are typically cleared in advance of the operating time. Some markets may close more than 60 min before the operating hour, and market clearing may still occur 5–30 min ahead. While the accuracy of forecasts in these horizons tends to be far better than those used in the day-ahead market, they are still not easy to compute. Precise forecasts during this timeframe are critical to ensure the operating reliability and economic dispatch of all of the technologies. A poor forecast in system operation can also have severe economic, financial, and reliability consequences. This may depend on the forecast horizon and market where it occurs as well as the magnitude of the forecast error.

The reliance on accurate forecasting and its impact will continue to increase in importance (see Figure 2) as variable renewable energy installed capacity grows. Unit commitment procedures may decline in importance due to decreases in resources that require ample time to commit. However, the decision to charge batteries and other storage is heavily impacted by the forecasts of prices, which are driven by the predictions of everything else. Price-responsive demand also requires accurate forecasts to position a plant to react to price events while minimizing the impact on its operations and resources.

Load, renewable energy, and fuel forecasts are used to derive a series of other predictions. These will impact future prices, thereby affecting offers of fuel-limited resources, such as natural gas and energy storage. Contingency analysis is driven by forecasts, as the possibilities that system operators are most worried about may not simply be single events. Increasingly, they could be extreme, weather-driven, multiple-contingency occurrences. Dynamic transmission limits require forecasts to ensure the changing resource mix can be most efficiently used, extracting the most possible out of a potentially constrained transmission system.

Dynamic operating reserve requirements are forecast so that sufficient quantities are ready when risk is high but reduced when it is low to keep costs down. Finally, forecasts are required to help anticipate extreme events that may have devastating impacts on the power system. With a changing climate, forecasting techniques will need to evolve to incorporate these shifting conditions from the planning to operating timeframe.

The Integration of Renewable Energy Into Market Operation

Increasingly, renewable energy generation assets are asked to participate in electricity markets and compete against

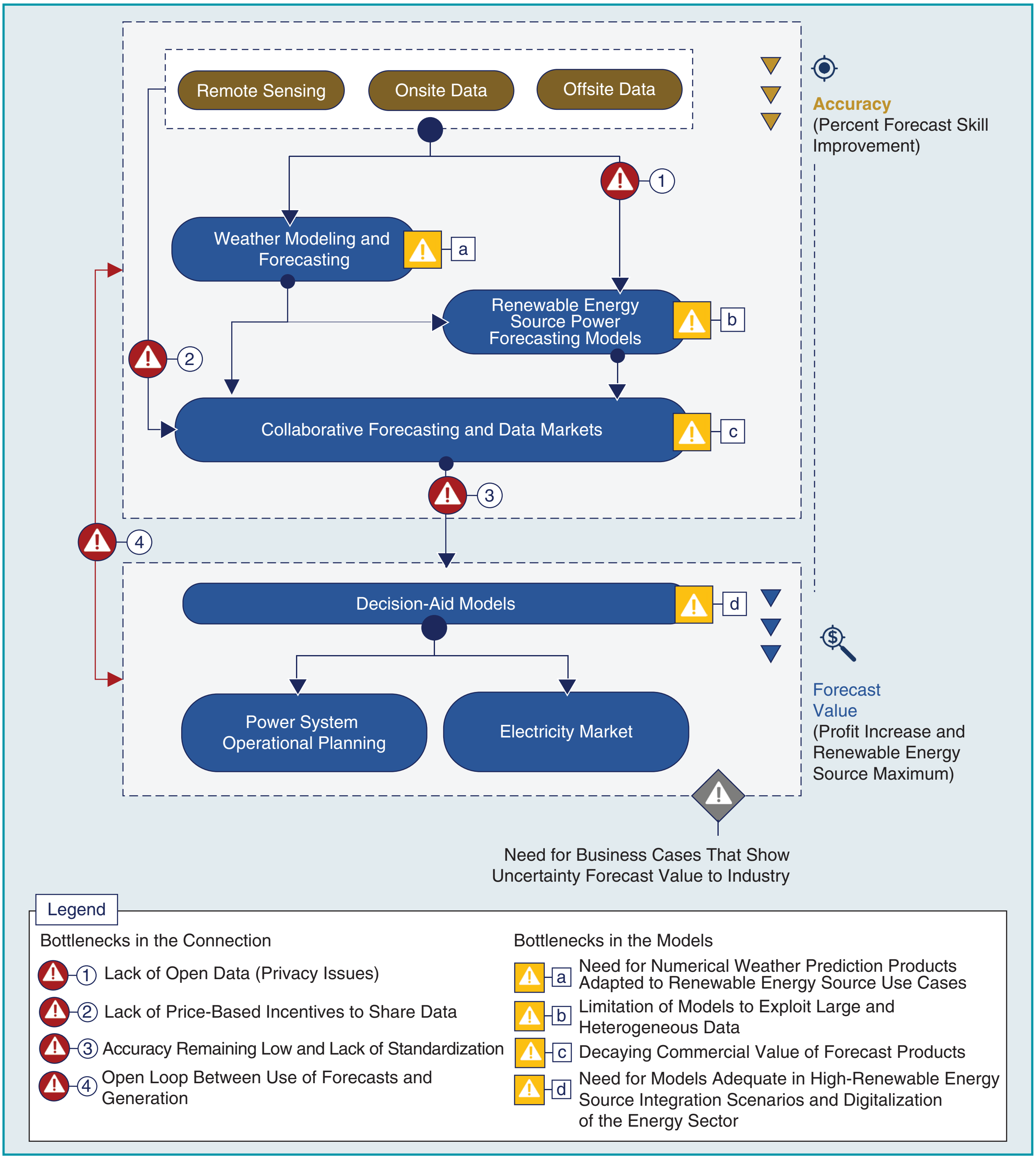

figure 1. The current bottlenecks of the renewable energy forecasting value/model chain. (Source: Smart4RES project; used with permission.)

other forms of power generation, with or without additional regulatory support. In most cases, those electricity markets comprise several forward stages (e.g., day ahead) and a near-real-time balancing stage. Consequently, renewable energy producers (or portfolio managers) place offers in those forward electricity markets based on forecasts.

Market participation has been the main motivation for renewable energy producers to invest in forecasting solutions over the last few decades. It has also been a strong driver for innovation in forecasting and for assessing the value of competing forecast solutions. For instance, besides the problem of the quantification of reserve requirements (discussed later in this section), market participation supported the focus on uncertainty quantification in renewable energy forecasting and eventual advent of probabilistic forecasting.

Today, emphasis is placed on many problems related to the market participation of renewable energy producers. These are all problems of decision making under uncertainty since the power generation forecasts are not perfectly accurate. One of the most basic considerations is that the market-induced penalties for imbalances may not be symmetric, e.g., the penalty can be higher for underproducing than overproducing. This incentivizes being strategic when placing offers in electricity markets.

In addition to such uncertainty-related considerations, one should be aware of risk-related considerations. Forecast errors may vary greatly, most often being small but sometimes very big, and so may market prices and induced penalties. As a result, revenue losses may become very large, though infrequently. This has motivated the proposal of risk-aware market participation strategies, which are similar to those in financial markets. With the increasing importance of storage in energy systems, hedging may come from operating additional assets instead of being based only on market participation strategies.

Forecasting Use Cases for System Operation and Markets

If the net load is underestimated, there is the potential for large costs or load curtailments. Conversely, if it is overestimated, there is a relatively mild increase in operating expenses. The asymmetric costs of errors are the major reason operators should (and do) recognize risk in making decisions. Simple rules of thumb are inadequate to manage risks when variable renewable energy is providing 30%, 50%, or even more of the supply. Over the past decade, researchers and vendors have developed powerful tools that allow operators to explicitly quantify probability distributions of the net load that reflect current as well as future weather and consider them in operations decisions.

Probabilistic forecasts of the wind, solar, and consumer components of net load can be divided into two basic types:

- ✔ The first is a marginal probability distribution of a single variable, such as net load or one of its components, at a particular time and specific location or system, conditioned on available weather information.
- ✔ The second is a multivariate characterization, accounting for dependencies either over time (such as the evolution of wind over the day), space (for example, the diversity of solar resources over a region at a particular time), or components (accounting for wind, solar, and load correlations). These characterizations can be in the form of formulas for joint distributions or, more commonly, a set of possible scenarios, such as an ensemble of NWP forecasts.

Some of the simpler ways in which these probabilistic forecasts can be used include setting reserve requirements, where the amount of procured reserve is based on an a priori tolerable risk level—such as covering 95% of occurrences or

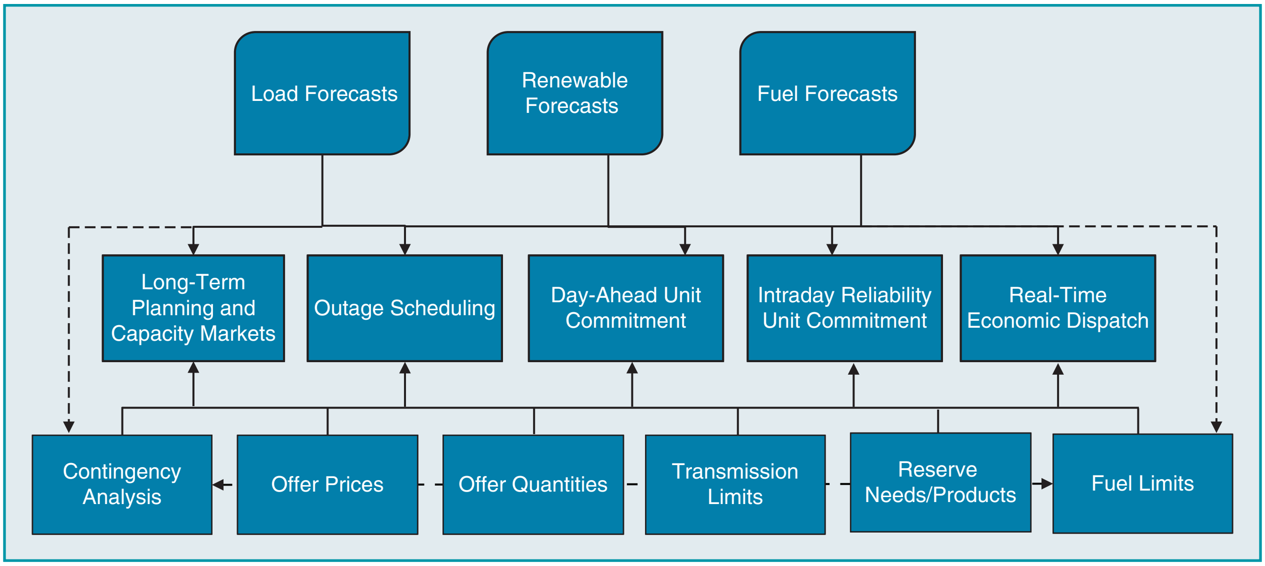

figure 2. The evolution of forecasting applications: load, renewable energy, and fuel predictions will be used to develop other forecasts of increasing needs in the future.

a more sophisticated balancing of costs and risks from different reserve levels. Another example might be constructing market offers for renewable output based on a preset risk level, for instance, as is commonly reflected in the value-at-risk limits to which traders are subject.

Figures 3 and 4 give an example of how probabilistic solar predictions for a particular time and place, the simplest type of forecast, are useful for informing the selection of a reserve requirement based on a preset probability of exceedance. The figures show how forecasts of the degree of uncertainty in solar power could be used to develop weather-conditioned requirements for the California Independent System Operator (CAISO) real-time flexible ramp product. In particular, they show how the width of the 50th percentile of global horizontal irradiance (GHI) derived from 2-h-ahead probabilistic forecasts, such as those in Figure 3, could inform ramp requirements.

The CAISO's flexible ramp product procures spare capacity in upward and downward directions to accommodate not

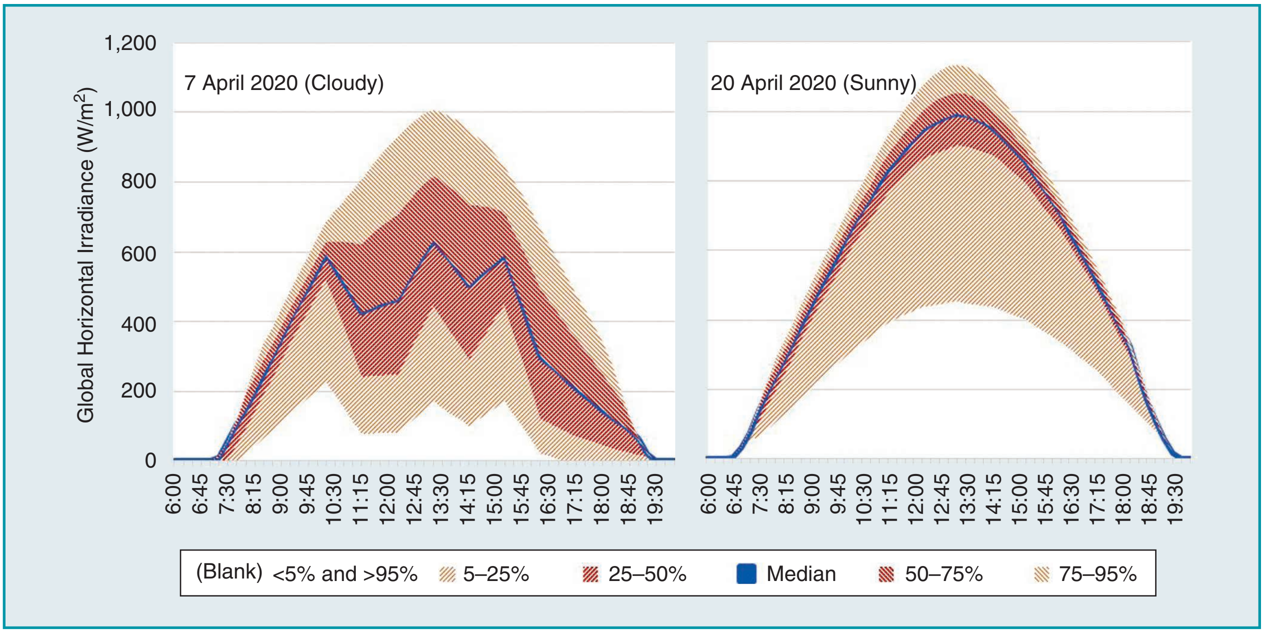

figure 3. A site-specific, 2-h-ahead probabilistic global horizontal irradiance forecast [7 and 20 April 2020, site location: Los Angeles, California], generated by the Watt-Sun probabilistic forecasting system. (Source: IBM; used with permission.)

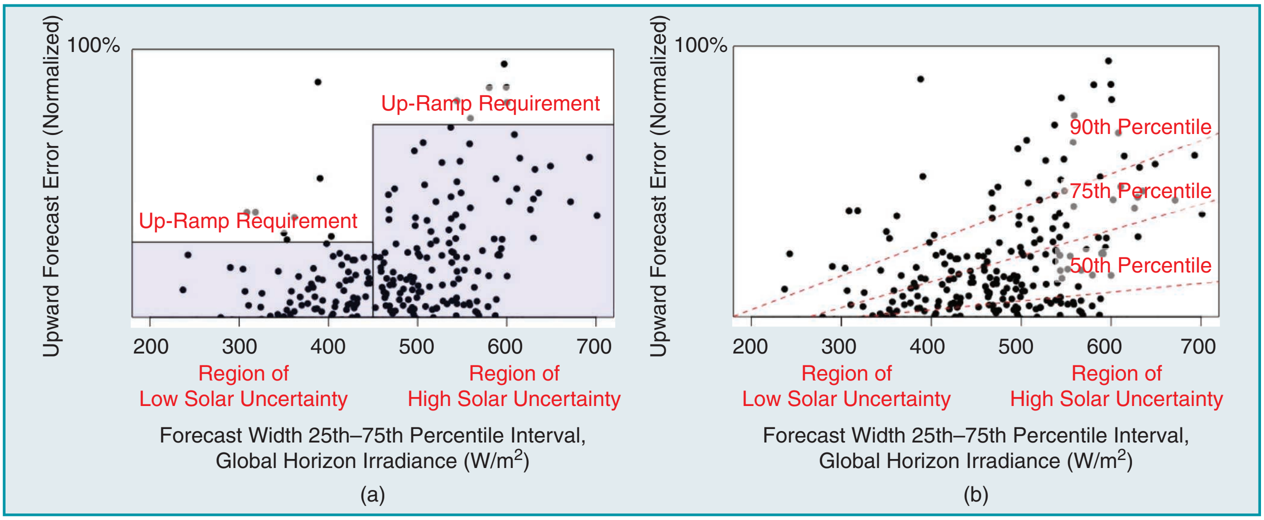

figure 4. (a) An example of the classification of days into two types (low and high solar uncertainty, based on 50% prediction intervals for the forecast global horizontal irradiance) and dependence of upward real-time ramp uncertainty (from 11 a.m. to 2 p.m., May 2019, the CAISO system). The ramp requirement is based on the 95th percentile within each classification. (b) An example of the quantile regression relationship between GHI uncertainty (50% prediction interval from the forecast) and upward CAISO real-time ramp error. Three estimated quantiles are shown for ramp error (90, 75, and 50%). (Source: Yijiao Wang; used with permission.)

only net load ramps in the real-time market but also uncertainty in both directions. The process proposed in Figures 3 and 4 exploits a statistical relationship between that index of GHI uncertainty and the 90th or 95th percentile of forecast ramp errors in the upward direction (i.e., underestimation errors used to specify the amount of flexible ramp product).

Figure 4 shows two such relationships that could be used for this purpose. These relationships can be derived, for instance, by classification [Figure 4(a)], quantile regression [Figure 4(b)], or machine learning methods. Production cost simulations have shown that such a process can potentially reduce the average procurement expenses while improving system reliability. The next three sections describe other applications involving the use of probabilistic forecasts to inform operating decisions. First, how such forecasts can be used to help manage extreme weather events is discussed, followed by explorations of how forecast information can be used to set regulation requirements in daily markets and perform week-ahead resource assessments, and then closing with a discussion of needed innovations and research.

Managing Extreme Events

As evidenced by the recent cold wave that brought days of outages to the Texas interconnection, the electric system has always been significantly impacted by weather. Temperature and humidity are primary modulators of demand. Temperature also affects transmission capacity limits, thermal and renewable unit capacity ratings, and generator outage rates. Wildfires, wind (including strong winds or rare extreme events, such as convective downbursts), ice, and lightning all impact transmission and distribution systems. In the case of fires, the resultant smoke and dust also significantly reduce PV output.

As the penetration of weather-driven renewable generation increases, weather dependence is increasing concurrently. It is also becoming more complex as additional weather variables (e.g., wind speed and insolation) interact with temperature, humidity, and precipitation to create nonlinear and nuanced relationships impacting both supply and demand. This requires an evolution of system planning, especially regarding how extreme events are handled.

The recent events in Texas illustrate that extreme events must be not only forecast in the operational time horizon but planned for in the system design phase, with a particular focus on what type of extreme events the system should be designed to handle. A perfect prediction of demand and renewable resources is not useful if generation is unavailable to serve the load due to outages or a lack of fuel (such as coal, gas, wind, or sun).

As wind and solar provide increasing proportions of electric generation, the nature of extreme events will evolve dramatically. This is illustrated as follows with an example that compares the famous February 2011 cold wave to a much weaker one that hit the central United States in February 2008.

The 2011 event saw almost a third of the nation experiencing temperatures below 0 °F (–18 °C), with numerous records being broken. The 2008 occurrence, while cold, was not an extreme, highly improbable event for the electric system by traditional metrics. However, a recent U.S. Department of Energy study into 2050 capacity scenarios showed that the 2008 event placed the Eastern Interconnection under more stress than the 2011 episode. This is because the available wind generation in the 2011 case is much higher than that of the 2008 example. Consequently, the net load (i.e., the total load minus the renewable generation) is much lower than that of the 2008 event.

Figure 5 shows the national daily wind capacity factor deviation from the normal for each day of the two events. It clearly illustrates that the available wind energy was much better in 2011 than in 2008, but it also shows large geographic heterogeneity and, thus, the importance of geographic diversity in capacity buildout. Despite the 2011 event featuring colder temperatures and higher loads, the load that needed to be met by nonrenewable sources was lower than for the 2008 event when modeled with 2050 generation infrastructure.

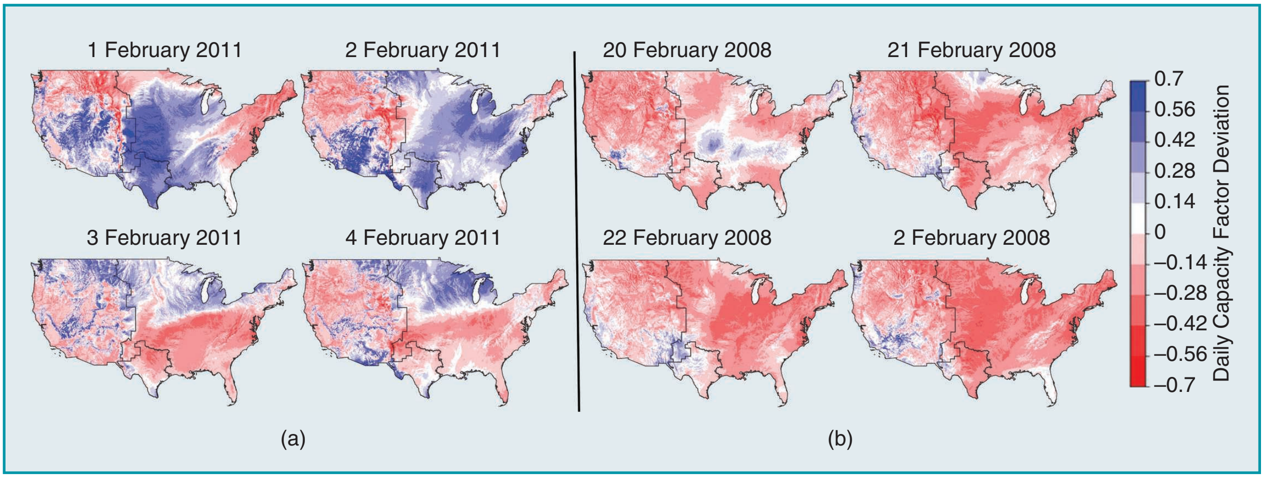

figure 5. The national daily average wind capacity factor comparison between the (a) February 2011 and (b) February 2008 events.

System operators need to be aware of this paradigm shift and understand that some weather events currently deemed benign will lead to system stress. The focus should not merely be on events that drive extreme loads, but, rather, it should shift to looking at events driving extreme net loads.

Smarter Procurement of Regulation Requirements at the CAISO

As renewable penetration grows on the CAISO system, it has become more important to develop methodologies to incorporate products into the CAISO market optimization to assist with uncertainty from the increasing capacity of renewable resources. The CAISO products to assist with uncertainty include regulation or operating reserves, flexible ramp requirement, and a new product in development: imbalance reserves. These can provide the flexibility needed to assist with forecast deviations or movement between different periods. For this discussion, the focus is on smarter procurement of regulation requirements or operating reserves.

Regulation requirements account for active power capacity held above or below expected average energy schedules to respond to changing system conditions under operational timeframes. For the California ISO, the focus is the prior 5 min to the current system condition. Regulation requirements are held for many reasons—maintaining frequency, reducing area control error (ACE), power plant contingencies, forecast error for demand, behind-the-meter generation, and large-scale renewable generation. In the past few years, the CAISO has partnered with multiple research partners to develop and trial methodologies to optimize the regulation capacity required during operating hours when the need is less but increase operating reserves when it is greater.

The current methodology utilized is based on a statistical analysis of the ACE signals and actual regulation applied to the system to correct ACEs. The sum of ACEs and actual regulation applied to the system to correct ACEs is referred to as *ACE**. The base statistical analysis is updated monthly at a minimum. Figure 6 shows the last 30 days of ACE* (red lines) in combination with the regulation recommendation (gray and yellow lines). The risk tolerance percentiles forming the regulation recommendation within Figure 6 are for the 98% (gray lines) and 95% (yellow lines) confidence bands. Note that the risk tolerance percentiles are configurable. If the CAISO finds that the regulation requirement recommendation hits outside the bands, impacting operational conditions, it indicates the potential need for adjustment of the risk tolerance parameter.

Figure 7 shows an additional tool that allows the CAISO to further analyze certain days and look at some of the main

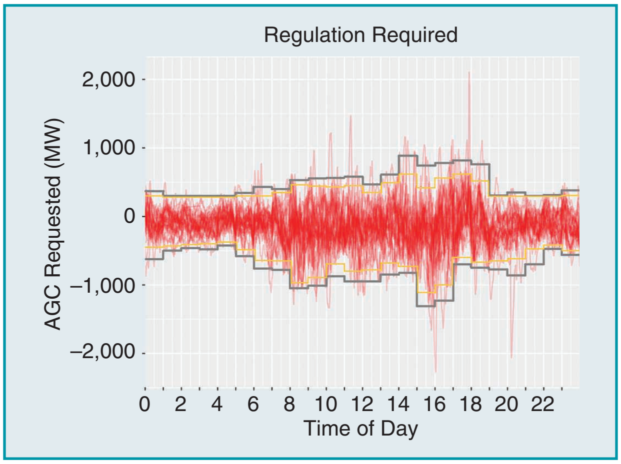

figure 6. An example of a monthly look at ACE* alongside requirement recommendations.

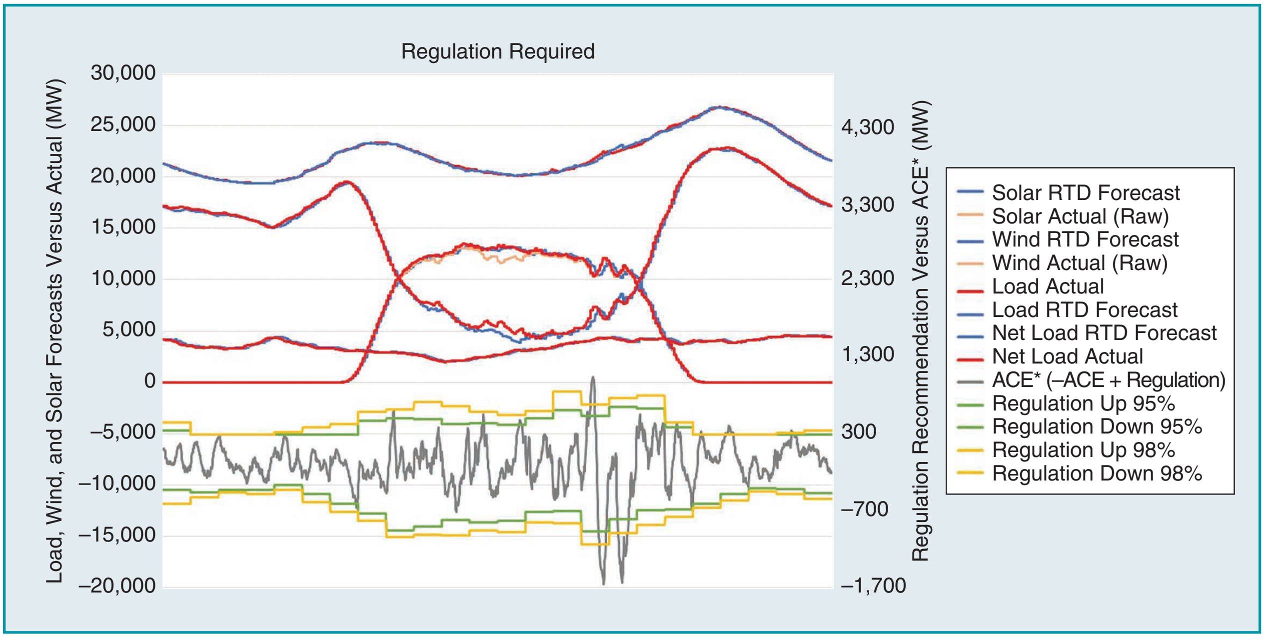

figure 7. A postanalysis from the perspective of the regulation needed for a day in March 2021. RTD: real time dispatch.

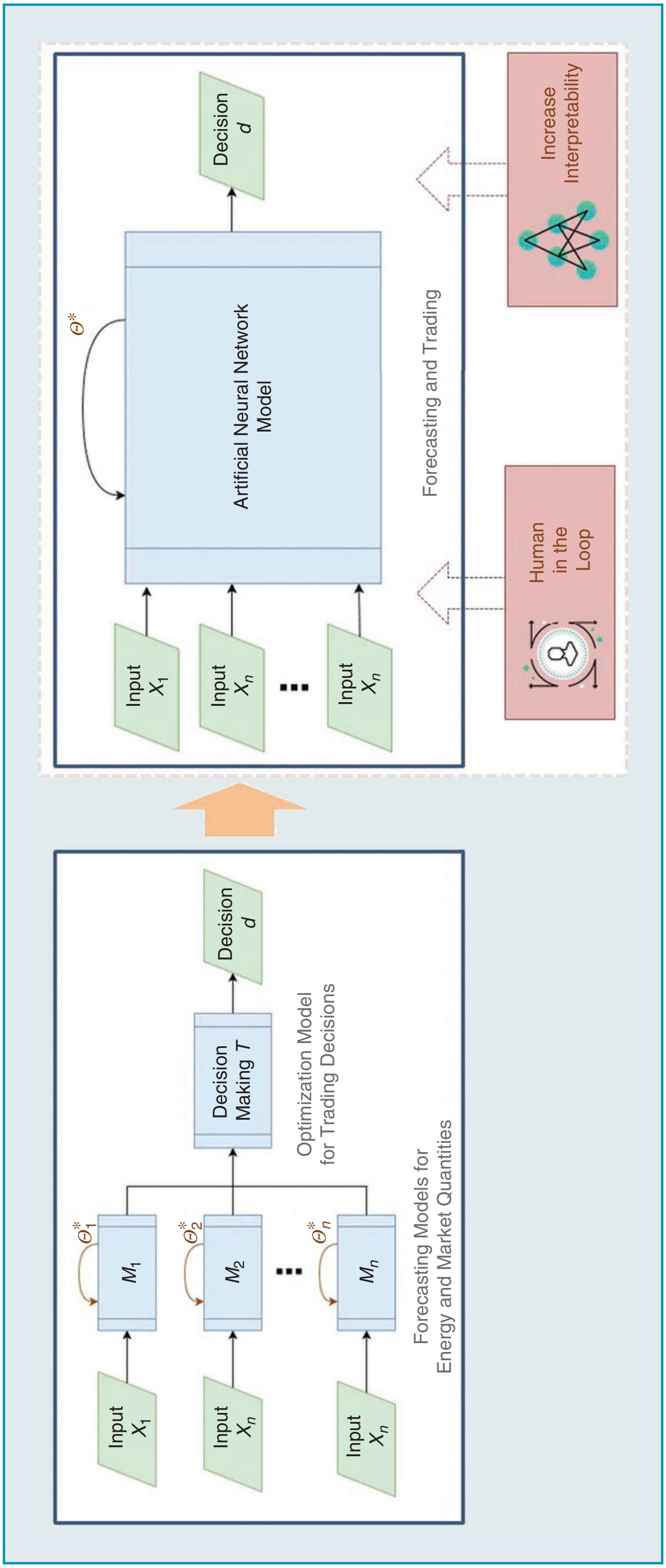

figure 8. The future evolutions in the model chain thanks to machine learning techniques. (Source: Smart4RES project; used with permission.)

drivers for regulation use [demand (blue/red), wind (blue/red), solar (blue/red), and net load (blue/red)]. The ability to see how individual days react gives further information about each weather pattern's impact on regulation requirements.

By implementing the ACE* methodology, the CAISO has seen 50–70% improvement in meeting the actual regulation requirement. This improvement was determined by looking at how many times ACE* is outside the regulation recommendation. The CAISO continues to explore smarter regulation procurement methodologies. In 2021, the CAISO plans to trial a methodology that utilizes both historical statistical information and probabilistic forecast information to compare the accuracy of the current methodology against the new options.

Accounting for Forecasting Uncertainty in the Week-Ahead Resource Assessment Process

The week-ahead resource assessment process is used to ensure there is a sufficient supply of electricity to meet the expected demand in the week ahead. Several factors influence this assessment, including plant or equipment outages, network constraints, and the expected level of demand.

Over the last decade, the east coast electricity grid in Australia has had an exceptional increase in the penetration of behind-the-meter rooftop PV installations, with one in three houses in some locations now having rooftop systems. The grid's generation composition has also seen significant change, with the installation of more than 22 GW of variable renewable energy capacity in a grid with a peak load of 36 GW. These differences have made the week-ahead resource assessment process increasingly sensitive to weather predictions.

The accuracy of the forecast inputs is increasingly driven by the expected weather conditions. For example, a large high-pressure system over continental Australia typically produces clear skies, light winds, and pleasant temperatures. These conditions are ideal for accurately predicting electricity demand as well as wind and solar generation, and uncertainty in the forecasts feeds into the week-ahead resource assessment.

Conversely, dynamic weather patterns, such as tropical cyclones, can produce fronts; patchy, fast-moving clouds; and gusting wind conditions. It is generally difficult to accurately forecast electricity demand as well as wind and solar generation for these conditions, and this leads to higher uncertainty in the forecasts feeding into the process.

Recognizing the increasing importance of understanding forecast uncertainty to the operation of a secure power system, in 2018, a change to the rules governing Australia's electricity system introduced a probabilistic assessment of the forecast inputs into the week-ahead resource assessment process. To account for the uncertainty inherent in each of the forecast inputs, the Australian Energy Market Operator developed a machine learning model (based on a Bayesian belief network) trained on more than 20 million data points of historic forecast errors.

Using the forecast weather conditions for the week ahead as input, the machine learning model gives a conditional probability of the expected level of forecast error under those conditions. The expected forecast error from the network is then used in the week-ahead resource assessment to indicate the amount of reserve generation above the predicted level of demand necessary to ensure a reliable energy supply.

Innovation and Future Research

The accuracy of operational renewable energy forecasting tools remains low in challenging situations such as evolving weather fronts. Improved accuracy translates into higher competitiveness of RESs in markets and more economically efficient and safe operation of the power system.

These factors stimulate intense research internationally in the field of renewable energy forecasting. Considering the model chain and associated gaps and bottlenecks shown in Figure 1, numerous directions of future research emerge. Some stem from new sources of available data (i.e., lidars, radars, sky cameras, and satellites), allowing better modeling of weather variables and RES production. NWP models may benefit from RES plants as distributed sensors for data assimilation.

RES forecasting models need to consider multiple data sources, in contrast to the mainstream approach, where tailored models are built upon for specific data sources (i.e., satellite images for PV predictions up to 6 h ahead). More general approaches may lead to a simpler model chain where forecasting models can cover multiple timeframes.

Beyond convergence in the temporal scales, models based on hierarchical forecasting are needed to enable the compatibility of predictions and associated uncertainty at different geographical scales. Recent work has shown that using data from neighboring RES sites improves the accuracy of a site. One of the related directions is to develop approaches for data sharing that respect privacy and confidentiality constraints, accompanied by data market concepts to facilitate and incentivize data owners to share their data.

Contributions from artificial intelligence techniques may support massive data flow processing. They can be used to develop prescriptive analytics for decisions (i.e., trading) based on the input data while replacing multiple forecasting and optimization steps, as shown in Figure 8.

Finally, new application use cases continuously appear where classical or new forecasting products are required. The main challenge is how to develop decision support tools that efficiently account for the inherent uncertainties, a massive amount of streaming data, and features to support human-in-the-loop informed decision making. Multidisciplinary research initiatives are being undertaken that demonstrate the benefits of collaborative efforts to tackle the complex nature of these problems.

For Further Reading

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