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USING FORECASTING SYSTEMS TO REDUCE COST AND IMPROVE DISPATCH OF VARIABLE RENEWABLE ENERGY

TECHNICAL GUIDE

Cover Image A system in University of British Columbia (UBC) with pyranometer and pyrgeometer for meteorological observations related to solar insolation. UBC Climate Station. © UBC Micrometeorology/Flickr. CC BY 2.0.

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ACRONYMS AND ABBREVIATIONS

AEMO	Australian Energy Market Operator
AI	artificial intelligence
ANN	artificial neural networks
ARIM	auto regressive integrated moving average
ARMA	auto regressive moving average
CECRE	Control Center of Renewable Energies
EMS	energy management system
ESMAP	Energy Sector Management Assistance Program
GSEP	Global Sustainable Electricity Partnership
IEA	International Energy Agency
IT	information technology
kW	kilowatt
MEPSO	Electricity Transmission System Operator of Macedonia
MW	megawatt
NWP	numerical weather prediction
O&M	operations and maintenance
PV	photovoltaic
REE	Red Electrica de España
SCADA	supervisory control and data acquisition
SWM	support vector machine
VRE	variable renewable energy

All dollar figures denote U.S. dollars unless otherwise noted

TECHNICAL GUIDES ON VRE GRID INTEGRATION: PREFACE

Over the past ten years, the cost of technology for variable renewable energy (VRE) such as wind and solar energy, has declined considerably, providing a cost-effective and sustainable means of meeting electricity demand in developing and middle-income countries. Taking advantage of variable sources of energy requires significant expansion and modernization of electrical grids and implementation of VRE-specific technologies, processes and requirements to gradually transition power systems into "VRE-friendly" grids that will significantly reduce integration costs in the long term. The need for technical assistance on VRE integration is greatest in countries with limited capacity to tackle technical and regulatory challenges. To meet this growing demand, the Energy Sector Management Assistance Program (ESMAP) of the World Bank has prepared a set of technical guides that can help World Bank staff and clients understand some of the essential requirements and available technical and regulatory measures to integrate large shares of VRE into power grids without compromising the adequacy, reliability or affordability of electricity. The technical guides have been developed as a joint initiative between ESMAP's Variable Renewable Energy (VRE) Grid Integration Support Program and the Global Sustainable Electricity Partnership (GSEP). The Global Sustainable Electricity Partnership is a not-for-profit international organization comprising the leading companies in the global electricity sector who promote sustainable energy development through electricity sector projects and human capacity-building activities in developing nations worldwide.

It is projected for the next five years that annual worldwide addition of solar and wind energy will continue to grow and is likely to at least double compared to their current share in power systems. Modern renewable energy generation technologies provide a strong alternative for grid electrification in locations where renewable resources are abundant and are starting to become the least-cost option in many of the client countries thanks to rapid decline in prices. For this, many emerging economies have started to adopt policies to encourage the development of the industry to realize the benefits that renewable power generation can have for their energy supply and on the local environment. Solar and wind installations can be built relatively quickly, which presents a major incentive in rapidly-growing, emerging markets with urgent need for power and also tackle the realization of climate change commitments.

The key challenging issue, however, is the intermittent nature of solar and wind power, which increases the complexity of overall grid operations. The grid operators have to manage variability of the energy resource, reliability of grid operations and least-cost optimal performance. The fast penetration of renewable energy, and especially, a high level of their penetration into the power grid requires an adapted power system planning, better forecasting methods, introduces challenges in grid management, imposes stringent requirements for VRE integration into the grid, and necessitates standardization and structured process for the conducting studies to ensure compliance with the grid code requirements. The basic grid support services are becoming now relevant to all generators, including VREs, which are connected to medium and lower voltage levels. The modern electricity industry is restructuring with two major trends: significant increase of renewable energy and deregulation providing consumers with energy purchasing options of highly reliable delivery. However, deregulation, open energy access, and cogeneration are creating scenarios of transmission congestion and forced outages. Restructuring envisions the transmission grid as flexible, reliable, and open to all exchanges no matter where the suppliers and consumers of energy are located. The modernization of the grid requires the increased power quality, system stability, and increased transfer capacity of the transmission. New approaches to Power System Operation and Control are gaining the development momentum for overload relief and efficient and reliable operation. High-voltage direct current (HVDC) and Flexible Alternating Current Transmissions Systems (FACTS) technologies appear especially effective for improvement of grid operations and management.

The proliferation of smarter infrastructure, enabling participation of increasing amounts of demand in activities also help mitigate the variability of renewable generation along with technological advances of renewable and complementary technologies like batteries allow renewable generators themselves to effectively contribute to maintaining reliability. A variety of emerging end-use technologies like electrical vehicles, heat pumps, and smart and efficient buildings enable greater flexibility in power systems and lead to higher demand for wind and solar. These technologies help to enable even greater usage of VRE resources, but at the same time, they bring additional challenges of overall grid operations, which require new approaches to system operation and planning to ensure that the new trends contribute to clean, reliable and affordable power systems. A shorter dispatch cycles in combination with more accurate shorter-term forecasts of renewable generation can be used to reduce forecast variations from renewable generators and result in reduced ancillary service requirement. A look-ahead unit commitment and stochastic unit commitment can effectively deal with uncertainty. Wind farm can be tasked to provide frequency response, inertial response, and regulation if they meet eligibility requirements. Storage technologies are beginning to be gradually deployed or included in provision of ancillary services. Frequency regulation market, which awards quick-start and fast responding resources including batteries, has been attracting an increasing amount of battery storage and new ways of using storage. There are also ongoing innovations combining variable renewable production with measures aiming to make demand more responsive. The benefits and effectiveness of new emerging trends are well recognized, but there are yet to reach full maturity and become standardized. The focus of the technical guides is primarily on the industry proven technologies and methodologies, which have already been established, widely adopted, and continue to proliferate in electrical utilities. However, the discussion of some new VRE related technologies that have already started influencing the utility landscape (e.g. dynamic energy storage, implementation of superconducting materials in fault current limiting devices, advanced forecasting methodologies, wind farm synthetic inertia and regulation response) are selectively included in the technical guide material where appropriate.

The information presented in the technical guides is compiled from various sources of information to serve as a high-level guidance and quick reference for the World Bank personnel on electrical power system projects involving implementation of VRE along with associated technologies and analysis. The technical guides are comprised of the following four sets of sub-documents, which are identified as the subjects of prime technical interest for VRE implementation:

- Grid Integration Requirements for Variable Renewable Energy
- Compensation Devices to Support Grid Integration of Variable Renewable Energy
- Studies for Grid Connection of Variable Renewable Energy Generation Plants
- Using Forecasting Systems to Reduce Cost and Improve the Dispatch of Variable Renewable Energy

"Grid Integration Requirements for Variable Renewable Energy" document presents a general overview of VRE technology along with some recommendations for VRE technical specifications, applicable standards, and essential testing. The main focus of the document presents a detailed outline of the essential requirements of VRE power plants integration into power grid. The different levels of VRE penetration in the grid determine different technical requirements for VRE integration. However, some of the requirements are fundamental and need to be respected for a VRE integration in any power system, e.g. regulation and automatic response to grid events, power quality, protection system, forecasting and analysis. The basic and advanced VRE integration requirements are discussed in detail in this document in order to provide a guiding reference for VRE projects regardless of the grid code's maturity. All essential requirements in the grid are summarized in the checklist table and can be used in course of VRE's project planning, implementation, and connection to the grid. The compliance with the technical requirements and grid code where applicable is validated through extensive series of interconnection studies such as steady state analysis, short-circuit and circuit breaker duty review, dynamic stability, and facility studies.

"Compensation Devices to Support Grid Integration of Variable Renewable Energy" document provides an overview of FACTS and other compensation devices along with the essential characteristics describing industry need, applicable standards, functionality, applications, and recommendations for minimal technical specification. The main objective of the document is to discuss all available FACTS technologies with the underlying concept of independent control of active and reactive power flows, the essential differences and benefits of FACTS devices, and industry applications. Classification and comparison of performance factors are analyzed in detail and summarized to orient the reader in the wide spectrum of FACTS devices, and their effects on the power system. The applications of FACTS devices are associated with the following essential technical enhancements: System Capacity, System Reliability, Power Quality, System Controllability. Environmental benefits of FACTS are obtained through the deferral of the construction of much more expensive transmission lines and better utilization of existing system assets.

"Studies for Grid Connection of Variable Renewable Energy Generation Plants" discusses the power system studies requirements for the stable grid integration of renewable energy plants. These requirements differ depending on the size of generation, the location of the connection, and whether it is transmission or distribution system. The main purpose of screening studies involved in the interconnection process is a successful integration of the VRE into the grid. Power system planning for interconnection of new variable generation resources ensures that there are sufficient energy resources and evacuation capacity to interconnect new supply, and that demand requirements are met in a reliable and efficient manner. Also, the studies verify that adequate reserves and necessary system resources exist to reliably serve demand under credible contingencies such as the loss of a generating unit, a transformer, or a transmission facility.

"Using Forecasting Systems to Reduce Cost and Improve the Dispatch of Variable Renewable Energy" document discusses the need and benefit of forecasting capabilities and how it is becoming more relevant to both system operators and large-scale VRE generators. Forecasting solar or wind generation over a timeframe of days, hours and minutes before real time power system operations can reduce balancing costs, minimize VRE curtailment levels, improve system reliability and ultimately increase the penetration of VRE sources in the energy mix. The main objective is to focus primarily on the types of forecasting methods and how physical and statistical models are used for developing short- to long-term forecasts. Good forecast helps to reduce the gap between contracted supply of power and actual provision of power, reducing imbalance costs for the generator. Essentially, an effective forecasting system helps move the entire power system closer to a fully merit-order dispatch system, with reduced uncertainty and costs around variable generation supply. Technological advances in weather forecasting, which, together with better data on historical performance of renewable energy, allow significantly improved forecasting accuracy of renewable generation, which results in a more efficient utilization of VRE.

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The Technical Guides on VRE grid integration is a joint initiative by the Energy Sector Management Assistance Program (ESMAP) of the World Bank and the Global Sustainable Electricity Partnership (GSEP). GSEP is a not-for-profit international organization made up of the leading companies in the global electricity sector that promotes sustainable energy development through electricity sector projects and capacity-building activities in developing countries.

This Technical Guide is part of ESMAP's variable renewable energy (VRE) grid integration support program. This global program helps World Bank client countries achieve the cost-effective and sustainable scale-up of VRE by providing technical assistance, capacity building, and knowledge products for the development and implementation of planning, regulatory, market, and operational best practices in VRE integration.

The document on **"Using Forecasting Systems to Reduce Cost and Improve Dispatch of Variable Renewable Energy"** was written by a team comprising Silvia Martinez Romero (Task Team Leader and Senior Energy Specialist, ESMAP); Chong Suk Song (Energy Specialist, ESMAP); Fernando de Sisternes (Energy Specialist, ESMAP); Martin Schroeder (former Energy Specialist, ESMAP); Sandra Chavez (Consultant, World Bank); Varun Nangia (Consultant, World Bank); Chris Edward Jackson (Consultant, World Bank); Fabian Koehrer (Consultant, World Bank); and external experts Claudio Pregagnoli (Enel Green Power), Eric Desrosiers (Hydro-Québec), and Julien Choisnard (Hydro-Québec).

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EXECUTIVE SUMMARY

The share of variable renewable energy (VRE) generation is rapidly increasing in power systems across the world. Developing countries are seeing unprecedented levels of new installations, thanks in large part to cost reductions and technological developments.

The uncertainty and variability of solar and wind generation, caused by fluctuations in wind speed and solar irradiation, present challenges for system operators as VRE penetration levels increases. This Technical Guide explains the role of VRE forecasting, in order to provide guidance to developing countries that implement it.

Successful implementation of an advanced forecasting systems is a cost-effective way to facilitate the integration of larger shares of solar photovoltaic (PV) and wind generators. VRE forecasting helps identify the amount of power that wind or solar PV generators will feed into the grid over the next minutes, hours, and days. Implementing forecasting into power system operations can reduce balancing costs, minimize VRE curtailment levels, reduce penalties for generation, and improve system reliability.

Forecasting provides system operators with sufficient advance notice to increase or reduce power output from other sources in the face of an expected shortfall or high level of production from renewable sources. For a plant operator, a good forecasting system can help reduce the gap between contracted supply and actual provision of power, reducing imbalance costs for the generator. More accurate forecast models can also allow a generator to bid more confidently and closer to the nominal installed capacity of the plant.

VRE forecasting models convert meteorological variables and/or historical generation data into an estimate of the plant's energy output at any given time horizon. A well-designed system integrates physical methods (which model the atmosphere, relying on weather data to calculate the right meteorological inputs) and statistical methods (which use time series and historical generation data to identify patterns) to project plant output.

Forecast accuracy is critical to understand the certainty of upcoming predictions and better inform decision making. It is affected by factors, including the siting of the plant, the forecast time horizon, local weather conditions, the geographic scope, data availability, and data quality.

Different factors affect the forecasts of solar- and wind-produced energy. Clouds are the primary challenge for solar forecasts; terrain complexity is the main factor affecting wind forecasts. Better models and more historical data are increasing the accuracy of VRE forecasts. For wind energy, hour-ahead forecasts have reach impressive levels. The mean absolute error of a regional wind energy forecast can be as low as 5 percent for the day-ahead and 3 percent for the hour-ahead forecast (Vaisala 2015).

Depending on the design of the system, forecasting can be carried out centrally (by the system operator), in a decentralized way (by the VRE generator), or by a combination of both. Combining centralized and decentralized forecasts is recommended because of the complementarity of the information the system operator and plant operator provide.

Countries can develop a forecasting system in-house, purchase a system from a commercial provider, or contract with company that provides forecasting as a service. Each option has advantages and disadvantages.

1| INTRODUCTION

Renewable energy is playing an increasingly important role in power systems. It experienced a record year in 2017, when renewables accounted for an estimated 70 percent of net additions to global power capacity (REN21, 2018). The increase was driven largely by new additions of solar photovoltaic (PV), which accounted for 55 percent of newly installed renewable power capacity, as well as increases in wind energy. In many countries, the share of variable renewable energy (VRE) generation is expected to be much greater in 2023 than in 2017, with a large shift of countries transitioning from 5–10 percent to 10–20 percent penetration of renewables. Most VRE generation will occur in countries with VRE shares of 10–20 percent (IEA 2019).

Accurately forecasting wind and solar generation is a cost-effective operational solution for managing the variability and uncertainty of power systems and enabling its integration (ESMAP 2015). Forecasting can help understand and predict the output of VRE generation over time, improving the ability to anticipate when additional generation sources will be needed or generation output from other sources would need to be reduced to ensure that renewable generation is not curtailed. By providing schedules for the availability of dependable capacity (the system's ability to carry the electric power for the time interval and period specified), forecasting can also help plant operators ensure that the renewable source can participate effectively in an energy market. A well-designed forecasting system reduces the uncertainty of plant output by attempting to predict the output of renewable power plants. Such forecasts reduce the need to keep high-cost generation sources online as primary reserves and ensure that when renewable resources are plentiful, more expensive generation is ramped down or taken offline.

This Technical Guide describes VRE forecasting (including types, models, and strengths) and the development and implementation of forecasting systems. It provides insights that can be used to deploy forecasting as a cost-effective tool for integrating VRE power into grids.

The Guide is organized as follows. Section 2 describes the role and benefits of forecasting. Section 3 describes the methods used to forecast VRE. Section 4 examines the design and sourcing of a forecasting system. Section 5 summarizes the Guide's main findings.

2 | THE ROLE AND BENEFITS OF FORECASTING VARIABLE RENEWABLE ENERGY

System operators must balance ever-changing loads with generation in real time. They need to know what the load is at any given point in time and ensure that adequate generation is available to meet demand.

With traditional dispatchable sources, it is possible to increase generation output to meet increased demand and reduce (or even turn off) generators in periods of low demand. Generation and reserves are scheduled in the day-ahead energy market in order to balance supply and demand. As increasing amounts of nondispatchable renewables come online, system operators face an additional challenge in matching supply with demand, in order to avoid curtailment of renewables, load shedding, or poor-quality power supply.

VRE forecasting[1] helps identify the amount of power that wind or solar PV generators will feed into the grid over the next minutes, hours, or days. It converts meteorological variables (solar irradiance and wind speed) into solar and wind power outputs. To do so, it uses physical and statistical models to assess the meteorological variables or historical generation data and estimate the total plant energy output at different time horizons.

Accurate VRE forecasting contributes to more economical, stable, and reliable operation of power systems. It is a relatively inexpensive strategy to enable higher VRE offtake. System operators have sought forecasting systems that enable better integration of VRE and lower integration costs since the very first wind and solar PV plants joined the system. Generators have also looked to advanced forecasting systems to help maximize the use of solar PV and wind plants and increase participation in power system dispatch.

Incorporating VRE forecasting in a power system benefits stakeholders by helping ensure that the power system is balanced. For system operators, a forecasting system provides a very valuable service—sufficient advance notice to either increase power from other sources in the face of an expected shortfall from renewable sources or reduce output or turn off other sources during periods of high VRE generation. It helps move the entire system closer to a fully merit order–dispatch system, with reduced uncertainty and costs around generation supply.

Considerable improvements have been made in recent years to decrease forecast errors, which reduces the requirement of having online generators to provide the regulation support in short-term operation and standby generation in medium- to long-term operations. Forecast errors are typically 3–6 percent of rated capacity one hour ahead and 6–8 percent for day ahead on a regional basis (Bird et al. 2013).

Forecasting can significantly reduce system costs if it is effectively incorporated into the system's day-ahead and week-ahead planning and operations. Day-ahead generation forecasts can be used to make

[1] The basic process is applicable to other renewables with low dispatchability and high variability, such as tidal or wave power. Output changes of such plants are relatively predictable and fewer and smaller plants are in operation. Hydroelectric power plants are outside the scope of this document. Long-term climatology plays a greater role in determining hydropower output than short-term weather events.

day-ahead unit commitment decisions, resulting in operational efficiency and cost savings. Short-term forecasts inform the amount of support from a quick-start generator, demand response, or other flexibility or mitigation options (Bird et al. 2013).

Forecasting systems can dramatically reduce system costs, which would be further reduced by faster scheduling and dispatch to cope with the intra-hourly variability of solar and wind plants (BOX 2.1).

BOX 2.1 Examples of reducing system costs through forecasting

According to data from several wind integration studies compiled in the report *Meeting Renewable Energy Targets in the West at Least Cost* (Regulatory Assistance Project 2012), forecasting could save up to $160 million in California (for 12.5 GW of wind power), $95 million in New York State (for 3.3 GW of wind power), and $510 million in Texas (for 15.0 GW of wind power). The same report also states that day-ahead variable generation forecasting would reduce operating costs by $5 billion a year in the Western Interconnection system (WECC) spanning Canada and the United States (Regulatory Assistance Project 2012).

A survey of more than 100 integration studies reports that on average forecast errors cost about $6/MWh. As penetration of renewables (particularly wind) increases to 30 percent, the cost of forecast errors can rise as well, approaching $9/MWh in one location in the United States. Estimates vary across countries and locations. In Ireland, for example, the cost averaged €3/MWh with wind penetration above 35 percent; in the Netherlands the cost was less than £0.5/MWh (Hirth et al. 2015). On the integration costs requirements, studies have shown that five- or 10-minute scheduling and dispatch have integration costs of $0–$4/MWh, whereas hourly scheduling and dispatch has integration costs of $8–$9/MWh or higher (Bird et al. 2013).

Xcel Energy, a utility serving customers in eight U.S. states, produces almost 30 percent of the electricity it supplies to its 3.6 million customers comes from renewable sources. Since 2009 it has used WindWX, one of the most advanced wind-production forecasting systems in the world. WindWX helped increase the company's wind forecasting accuracy by 39 percent. Better forecasting and other operational improvements saved customers $66.7 million in fuel costs through the end of 2016.

Examples of estimates of cost reductions in developing countries are limited and less detailed than examples from developed countries. Although the data are limited, they unambiguously show that even modest improvements in forecasting can result in significant reductions in integration costs—and the results are robust over a variety of VRE technologies, penetration levels, and costs.

In Morocco, for example the World Bank–supported Clean and Efficient Energy Program financed the construction of a $5 million renewable energy dispatch center that included week-ahead, day-ahead, and hour-ahead forecasting for solar PV and wind plants. The relatively modest investment is expected to reduce day-ahead unit commitment costs by $10–$17/MWh of VRE (World Bank 2015).

VRE forecasting can help reduce the gap between the contracted supply of power and the actual provision of power, reducing imbalance costs for the generator. More accurate forecast models can also enable a generator to bid more confidently and closer to the nominal installed capacity of the plant, increasing the effective capacity factor of the plant. From a plant operator's perspective, having an effective forecasting system helps move the entire system closer to a fully merit order–dispatch system, reducing the uncertainty and costs of generation.

VRE forecasting can help facilitate the operation of the system and enable the deployment of renewables as a way to achieve carbon emission reduction targets. Several countries, including India (see Box 4.1), have imposed forecasting as a requirement for VRE generation at the plant level or require the VRE plant operators to submit an aggregated generation forecasts together with other plants. Some impose penalties for high forecast errors. In some cases, all generators above a certain capacity must be registered and monitored by central VRE forecasting to facilitate system operation with high renewable penetration (BOX 2.2).

BOX 2.2 Forecasting, controlling, and scheduling renewable energy generation in Spain

The Spanish transmission system operator Red Eléctrica de España (REE) established the first dedicated Control Center of Renewable Energies (CECRE). It is responsible for forecasting, controlling, and scheduling renewable energy generation. Thanks to the CECRE and advanced forecasting system, the utility can now reliably integrate high levels of renewable energy into the system, reducing the amount of CO_2 emissions.

Two features of the regulatory framework favor advanced VRE forecasting. First, VRE plants with generation capacities greater than 10MW must be connected to a centralized dispatching center (also called a *generation control center*) or establish their own predictions and execute the operator's orders in real time. VRE generators that charge the regulated tariff are asked to forecast the amount of power to be produced one day in advance (with a deadline of one hour before market closing time). In 2015 this capacity limit was reduced to 5 MW. The CECRE thus monitors and controls production from renewable generation facilities, or groups of facilities, with a power capacity greater than 5 MW.

Second, the generation control centers, which act as aggregators and are authorized as interlocuters with the system operator, provide the CECRE with real-time information about every facility every 12 seconds. Through real-time telemetry, the GCC report on the connection status, production of active and reactive power, and voltage at the connection point. If unacceptable situations in the system are detected, orders to non-manageable renewable facilities limiting their production is performed in less than 15 minutes.

To address the high penetration of renewables, the CECRE started receiving the tele-measures of all wind or solar plants with installed power greater than 1 MW. These measures are supplied as an input to the forecasting system. CECRE uses SIPREOLICO, a wind power prediction tool that provides forecasts for individual farms for up to a 240-hour horizon. The predictions, based on more than 800 neural networks, provide aggregated hourly forecasts for individual wind farms. Wind power forecast errors have significantly improved, declining from 12 percent for an hour-ahead forecast in 2008 to 4 percent in 2015. The tool has greatly helped the system operator improve the aggregated VRE forecast and reduce the amount of operational reserves it needs to commit for balancing and regulation.

Source: ESMAP (2015); Red Eléctrica de España (n.d., 2016).

3 | METHODS OR FORECASTING VARIABLE RENEWABLE ENERGY

Forecasting systems use meteorological variables or historical generation data to estimate the total plant energy output at any given time horizon.

Forecasting methods can be broadly divided into physical and statistical methods. Physical methods use weather data to populate a physical model of the atmosphere. Statistical methods use historical generation data to project plant output. Statistical methods work best for intra-hourly forecasts and up to three-hour ahead forecasts. Physical methods are used primarily for forecasting output beyond three to six hours, with some exceptions in solar, such as the application of total sky imagers for short-term forecasting for cloud prediction (Haupt 2018). In general, statistical models perform better for wind energy than for solar energy over short time horizons and physical models show better results for both wind and solar over long time horizons (Widén et al. 2015), because statistical models do not do a good job of predicting cloud coverage. Physical models sometimes used total sky imagers—digital cameras that produce high-quality images to show the entire sky to the horizon—for short-term high-resolution forecasting.

Hybrid forecasts combine results from forecasts produced by multiple methods in a single cohesive forecast, which is often more accurate than individual forecasts. TABLE 3.1 illustrates the types of forecasts available.

Forecasting models provide an estimate of the weather parameters at the plant site. Physical or statistical methods combine these forecasts with the power curve of a wind turbine or solar PV module—either in real-world use or from the theoretical estimate from the manufacturer—to convert them into accurate and useful data for system operators that reflect plant responses to meteorological forecasts (Foley and others 2012).

Forecasting Models Based on Physical Methods

Physical methods rely on weather data input (such as air temperature, pressure, and surface roughness and obstacles) to create a customized meteorological prediction that matches and represents local conditions. Such methods allow a ground-up estimate of power output based on the fundamentals of atmospheric science. Numerical weather prediction (NWP) models, remote sensing, and local sensing are examples of physical methods of forecasting.

Numerical Weather Prediction Models

NWP models use mathematical representations of the atmosphere to predict weather conditions based on current weather observations relayed from radiosondes or weather satellites. NWP systems have been widely used for forecasting variables such as temperature, humidity, the probability of precipitation, and wind.

NWP models can cover the entire world or a specific geographical area. The selected domain is broken up into a grid of areas, each of which is predicted separately using the atmospheric equations. The aggregated result is a forecast for the entire domain.

NWP models are run repeatedly with slightly different starting conditions, to reflect the chaotic nature of atmospheric equations and the uncertainty in measurement of local weather conditions. These additional runs, called *ensembles*, give an indication of the range of forecasts. They increase confidence in the forecast (Foley et al. 2012).

TABLE 3.1 Applications, methods, and resolution of forecasts for various time horizons

Time horizon	*Applications*	*Methods*	*Resolution/granularity*
Minutes to 30 minutes ahead	• Regulation actions (primary and secondary reserve) • Real-time dispatch • Electricity market clearing • Congestion management	• Persistence, statistical methods • Local sensing for individual plants	1–15 minutes
30 minutes to less than 6 hours	• Secondary reserve • Economic load dispatch planning • Load increment/decrement decisions • Intra-day market	• Local sensing • Remote sensing • Satellite imagery • Regional or global numerical weather prediction • Physical and statistical learning methods • Artificial intelligence methods	Hourly
6 hours to 1 day	• Day-ahead operations • Reliability assessment commitments • Operations and maintenance (O&M) operations	• Local sensing • Remote sensing • Regional or global numerical weather prediction	Hourly
1 day to weeks	• Scheduling of O&M operations • Unit commitment and reserve requirement decisions • Maintenance scheduling to obtain optimal operating cost	• Remote sensing • Regional or global numerical weather prediction with ensemble	Hourly

Source: Soman et al. (2010); Wang et al. (2011); and Zieher et al. (2015).

***Typical use*.** NWP models can help day-ahead forecasting. An ensemble NWP forecast can provide a range of expected output to help plan reserves. Longer time horizon forecasts can also be helpful in planning operations and maintenance (O&M) schedules. For example, maintenance of a gas-fired power plant could be deferred until after a rainy period, once solar generation is available.

***Limitations*.** Given the size of the discrete areas in even the most sophisticated NWP models—about 10 square kilometers in a high-resolution model—and relatively infrequent runs, it may be difficult to use an NWP model for real-time operations or to model individual plant output (Inman at el. 2013). As modern NWP models are computational representations, they are limited by available computing resources and must trade off the size of the domain, the spatial resolution of the discrete areas modeled, and the forecast horizon. Even the most advanced models are unable to accurately predict smaller features (such as individual clouds) with certainty. NWP models are not particularly useful for solar forecasting in the first three to six hours of most solar PV plants (Widén et al. 2015).

Bottom line. NWPs provide more accurate forecasts than remote sensing models over longer time horizons.

Remote Sensing Models

Remote sensing models can help provide good estimates of field conditions over a large area without placing a large number of local sensors. These models integrate information from satellite measurements of weather from sources such as the National Oceanic and Atmospheric Administration's Geostationary Operational Environmental Satellite Network for North and South America (NOAA Satellite Information System n.d.) or the MeteoSat network for Europe, Africa, and central Asia (EUMETSAT n.d.).

***Typical use*.** Remote sensing models capture weather trends over large areas—even entire continents. They can consequently be used to show forecasts through the medium term by illustrating cloud movement or weather fronts that can affect solar PV or wind turbine output.

***Limitations*.** Remote sensing models rarely provide the accuracy plant owners require. They are therefore usually used in combination with other forecast models. For solar forecasts, these models are less effective than others in identifying quick cloud changes (formation or dissipation).

***Bottom line*.** Remote sensing models provide a simple and cost-competitive approach to medium- to long-term forecasting of expected wind and solar output. High-resolution satellite imagery data can offer a cost-competitive approach to medium- to long-term forecasting of solar PV output.

Local Sensing Models

Local sensing models use weather data from various points at or close to the facility to reflect actual field conditions. They capture high-resolution spatial and temporal data to provide information on frequency fluctuations of solar irradiance, which NWP and remote sensing techniques cannot. Local sensing models require temperature measurements to accurately forecast generation output.

***Typical use*.** Local sensing is typically used in short-term or real-time forecasts to capture the impact of cloud movements on solar PV energy output and local weather patterns on wind output. For wind farms, such sensors may be anemometers placed around the farm or at an appropriate place upwind of the facility that captures the local micro-climate. Solar PV facilities can use pyranometers or sky imagers to provide 3- to 10-minute estimates of solar PV output by illustrating cloud size and movement.[2]

***Limitations*.** Sky imagers are of significantly decreasing value beyond approximately a 30-minute time frame and are expensive relative to most forms of very short-term prediction (Widén et al. 2015).

***Bottom line*.** Local sensing models can capture high-resolution spatial and temporal data to provide information on fluctuations in solar irradiance and wind.

[2] Pyranometers can be installed horizontally (to capture global horizontal irradiation) or at the same angle as PV panels (to directly measure global tilted irradiation, also called *plane of array irradiance*). Imagers are digital cameras that produce high-quality images that show the entire sky to the horizon.

Forecasting Models Based on Statistical Methods

Statistical methods rely on gathering large amounts of historical data and using them to train models to estimate the output of a VRE plant. They are based on patterns rather than mathematical models based on physical methods Statistical methods are often used to statistically adjust the output of NWP or other models based on physical methods. Statistical methods work best for intra-hourly forecasts and forecasts up to three hours ahead, making them important for load following and regulation. When combined with other methods, they may also have some value for longer-horizon forecasting (Widén et al. 2015).

Reference Model for Forecasting

A baseline method for comparison is required (the reference for the forecasting). It is used to predict the trend of the forecast using simple methods. This trend then becomes the reference for the more complex statistical approaches, which involve the incorporation of factors such as temperature, relative humidity, and cloud cover.

Persistence Model

Persistence models are the most typical and simplest form of statistical forecasting. In the classical persistence model, the forecast of the VRE plant for the next time interval will not change, assuming that conditions do not change between the current and the future time (Kleissl 2013). The model typically uses average power generation for the last hour or less, adjusted for the diurnal cycle (daily variation patterns) in wind speeds, irradiation, or temperature. Combining these data with the outputs from a meteorological forecast record (forecasted irradiance or ambient temperature, for example) can help build a model that estimates output based on a forecast.

There are several variations of persistence models. In a damped persistence model, additional factors are introduced to improve accuracy. For solar energy, new persistence models based on the stochastic aspects of measure energy signals are being developed that could complement the solar forecasting family. These models promise to be efficient and easy to implement, because they do not require a large volume of historical data (Voyant and Notton 2018).

***Typical use*.** A classical persistence model is typically used for intra-hour forecasts, particularly for wind, where accuracy can reach acceptable levels. Over the first 15–45 minutes, it is often difficult to surpass the accuracy of the persistence forecast (Haupt 2018). These models are rarely used for longer-term forecasts, as they rapidly lose predictive power when time horizons increase.

For solar PV plants, several months of hourly insolation data from pyranometers on the site of the plant can help determine what the output of a plant might be on any given day. Persistence models are most accurate when the sky is clear, because they need to estimate only direct and diffuse insolation at the plant. Given relatively limited forecasts but a robust statistical correlation, system operators can estimate the range of output with reasonable confidence (Inman et al. 2013).

***Limitations*.** Persistence model work well for intra-hour forecasts, when conditions do not change. Solar irradiance at the ground level and other related atmospheric phenomena are nonstationary, however; persistence models therefore perform poorly for time horizons involving appreciable variations in the diurnal cycle, limiting their use to intra-hour applications (Kleissl 2013). Large, spread-out facilities may be relatively unaffected in aggregate, but individual PV units may see significant decreases in output as clouds unevenly reduce insolation. Consequently, the accuracy of persistence models decreases rapidly for solar PV in cloudy conditions.

***Bottom line*.** Persistence models provide a reference or trend of the forecasting that is accurate in the very short term. They need to be refined by other statistical techniques or hybrid techniques for use in longer time horizons.

Time Series Modelling and Statistical Learning Methods

Statistical techniques are generally based on mathematical models, which can be classified into causal and time series forecasting techniques. Causal forecasting is used to identify relationships between variables. It depends on the accuracy of the input factors. Time series forecasting collects observations over a designated period of time and then predicts future outputs based on previous events.

The simplest time series model is autoregressive analysis, which is sometimes used as a reference model. Statistical methods that incorporate time series modelling include the auto regressive moving average (ARMA), the auto regressive integrated moving average (ARIMA), the Bayesian approach, and gray predictions (Chang 2014).

***Typical use*.** In most time series modelling, a baseline provides the trend of the forecast. Modelling refines the random fluctuations around the trend.

Time series modelling is usually combined with other methods to form more sophisticated models. Exogenous inputs should be included, if available, as they reduce the forecast error. In the case of solar forecasting, for example, the persistence method would provide the prediction of the clear-sky expected value; random fluctuations would be refined through different types of time series modelling. Because of the randomness of cloud coverage and the importance of capturing it in short-term forecasting, local sensing models such as sky-imaging data from ground-based sky imagers are also used to refine the forecasting. They can considerably improve short-term forecast errors, especially for solar forecasting.

***Limitations*.** A disadvantage of time series modelling is the need for a training period. Ideally, several months of data collection are required before deployment (the number of months depends on the short- and long-term variability of the micro-climate). Another disadvantage is the reliance on the experience of the modeler in finding optimal parameters for the method. This limitation can be effectively overcome by artificial intelligence methods (discussed below) (Kleissl 2013).

***Bottom line*.** Time series modelling can be used to refine physical methods or baseline methods, in order to reduce errors and customize the results for short-term forecasting. This method is more cost-effective than other forecasting methods but also data driven and intensive.

Artificial Intelligence Methods

Artificial intelligence (AI) methods can be used to identify the relationship between predicted weather conditions and the power output generated as historical time series. These methods are different from conventional time series–based statistical approaches. They are based on pattern recognition through the use of neural networks rather than regression models.

One of the most prevalent statistical learning models using AI is the artificial neural network, which has proven accurate for short-term wind forecasts and outperforms time series models at all time scales (Soman et al. 2010). Artificial neural network models recognize hidden patterns or relationships in historical observations and use them to forecast future values (Shi et al. 2011). Other AI methods include fuzzy logic, support vector machine, neuro-fuzzy network, and evolutionary optimization algorithms, to name a few (Chang 2014). Compared with statistical methods, artificial neural network models are simpler to construct, require less development time, and do not require explicitly defined mathematical expressions (Bhaskar et al. 2010).

***Typical use*.** Artificial neural network and support vector machine models are used primarily in machine learning methods. They are well suited to describe the intermittent nature of wind, because they consider the nonlinearity of wind power generation. AI methods are often used with other methods to improve forecast accuracy.

***Bottom line*.** AI methods are much more accurate than other statistical learning methods, because they model the nonlinear, intermittent nature of atmospheric conditions. They are generally used with other methods to increase forecast accuracy.

Forecasting Models Based on Hybrid Methods

Hybrid forecasts combine physical and statistical methods. They tend to be more effective and accurate than either method used separately, because they benefit from the strengths of each method over different time horizons. A system operator can use a hybrid forecast to cover the entire time horizon of interest, from real-time operations to week-long scheduling.

Hybrid models for solar and wind power are used in the following combinations (Chang 2014):

- physical and AI approaches (example: hybrid NWP and artificial neural network model)
- statistical and AI approaches (example: hybrid AMRA and artificial neural network model)
- alternative AI models (example: hybrid approach based on combination of artificial neural network with wavelet transform).

The ability to implement multiple layers of optimization in the forecast is one of the major strengths of these hybrid approaches, which combine the best features of physical methods with the accuracy and robustness of machine learning of the different statistical learning and AI methods. A system operator can combine these models and methods, depending on the geographical size and types of VRE in the system, or rely entirely on plant operators for expected outputs and charge imbalance costs back to the generator, depending on the market structure.

Forecasting Wind and Solar Power

Both wind and solar forecasts use models to predict variables such as temperature, humidity, precipitation, and wind. The methods and models used to forecast energy output from wind and solar PV are similar. Both types of forecast depend on the time horizon.

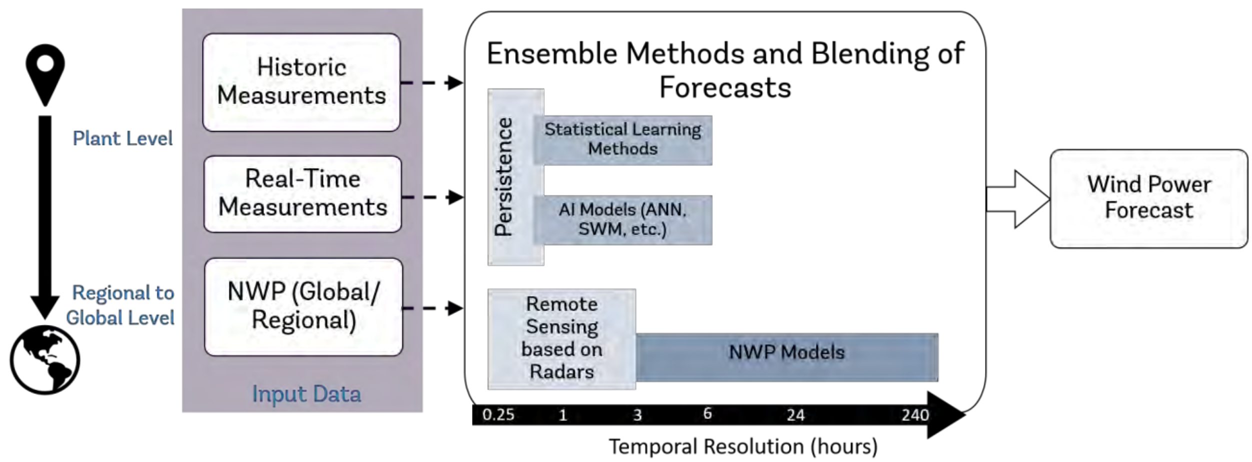
Forecasting Wind Power

Wind energy forecasting has been successfully implemented in many power systems, including in Denmark, Ireland, Spain, and Texas. Several commercial wind forecasting systems are on the market, and extensive research has been conducted on the subject.

To forecast wind power, it is crucial to calculate the wind speed at the hub height of the wind turbines in the most accurate manner. Wind power forecasting combines physical and statistical methods to cover different time horizons (FIGURE 3.1). A wind operator may use a persistence model for current conditions, remote sensing results for approaching weather fronts, an NWP model to predict wind speeds, and a physical method to build an accurate profile of turbine response to wind speed. Models can forecast the output of a wind for the next 48 –72 hours with a time step of 1 hour or for the next 6 hours in 15-minute intervals (Wang et al. 2011). Wind forecasting is used primarily for the immediate short term (minutes), the short term (hours to one day), and the long term (up to two days) (Wang et al. 2011).

Wind forecasting requires data history, often including several years of local field measurements, to capture the impact of terrain complexity on wind speed. NWP models are used to estimate wind output for the time horizons beyond three hours (add reference). NWP models cannot simulate all local details, such as variations in wind speed (Zieher et al. 2015). With the evolution of higher-resolution models, the simulation of details (such as fluctuations caused by changing wind conditions) is improving. Neural networks have been incorporated in wind forecasting, greatly increasing the forecast accuracy (see Box 2.2 for an example of wind forecasting that involves neural networks).

FIGURE 3.1 Framework for forecasting wind energy



Source: Adapted from Widén et al. (2015).

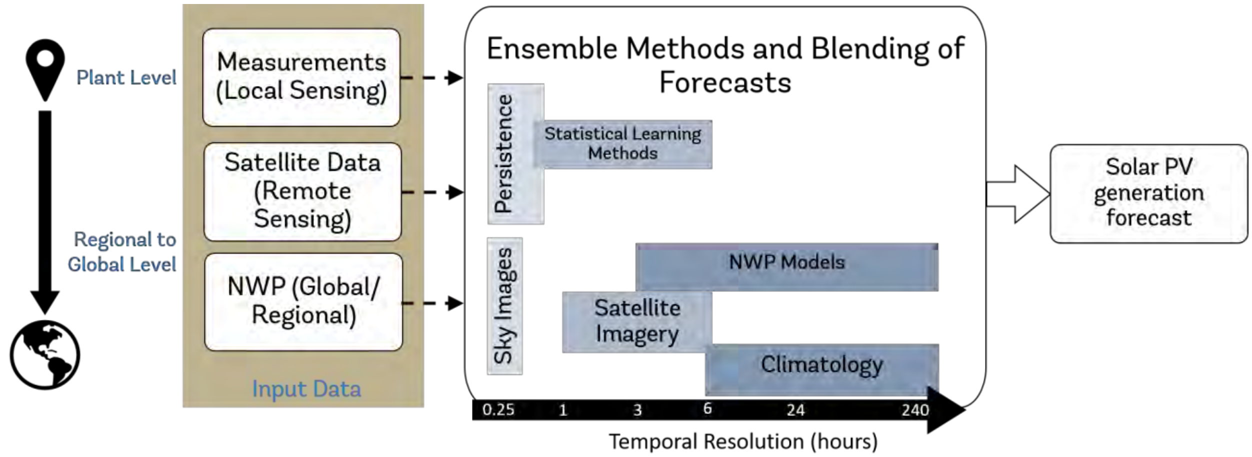
Forecasting Solar PV Power

Expansion of the solar market over the last decade has increased demand for accurate solar power forecasting. New tools have reduced forecasting errors, but solar forecasting is still a relatively new technology.

Much of the variability and uncertainty is related to quick cloud movement. The main challenge lies in estimating the influence that clouds, aerosols, and other atmospheric constituents have on the irradiance solar panels receive. Other differentiation is the diurnal variation of the sun. Large errors can be introduced during sunrise and sunset, when there are steep changes in irradiation (morning and evening ramps). These rapid changes can reduce solar plant output to a minimum within seconds to minutes. Solar forecasts also employ sky imagers and satellite imaging (data from networks of geostationary satellites to track and predict cloud formations at different timescales.

Using an ensemble of physical and statistical methods that show values for different time horizons increases the accuracy of forecasting solar generation. FIGURE 3.2 shows how a solar PV plant operator using a hybrid forecast might display local sensing results for current conditions; remote sensing results showing approaching weather fronts; and NWP model results, with an emphasis on cloud formation for forecasts longer than six hours. Statistical analyses can help a solar generator relate expected insolation to plant output.

FIGURE 3.2 Framework for forecasting solar energy



Source: Adapted from Widén et al. (2015).

Forecasts for distributed solar PV generation are more difficult to produce. They are most accurate when near real-time meteorological data and detailed static data (location, hardware information, panel orientation) are available for all interconnected systems.

Accuracy of Forecasts

Forecasting can significantly reduce the system cost of integrating renewables. The more accurate a forecast, the fewer reserves are needed and the less up and down regulation will be activated at the expense of the generator or utility.

It is important to evaluate the past performance of forecasts to understand the uncertainty of an upcoming forecast. Evaluation can be done either on demand by the system operator or automatically by an on-line performance-monitoring module.

The accuracy of a forecast depends on the accuracy of the weather forecast and the accuracy of the physical or statistical methods used to model output from the plant based on meteorological conditions. Factors that affect forecast performance and accuracy include the siting of the plant, the forecast time horizon, local weather conditions, the geographic scope, data availability, and data quality.

Table 3.2 shows the most commonly used metrics and indicative benchmarks of the errors of wind and solar plant forecasting. Solar PV and wind systems have opposite behaviors with regard to forecast errors. For a wind plant, a benchmark normalized mean absolute error, which varies depending on ambient conditions, is 6–12 percent for a six-hour horizon and 10–20 percent for day-ahead forecasts (Foley et al. 2012). For solar PV systems, clouds are the primary challenge. Incorrectly forecasting them can cause as much as a 30 percent error in an hour-ahead forecast but only about a 10 percent error out to four hours (Inman et al. 2013). These errors can be mitigated to a certain extent by using a combination of models. Other metrics can help disaggregate errors from inaccurate meteorological forecasts from errors associated with physical and statistical method issues that are within the purview of the generator or system operator.

TABLE 3.2 Common metrics used to assess forecasting error equations and benchmarks

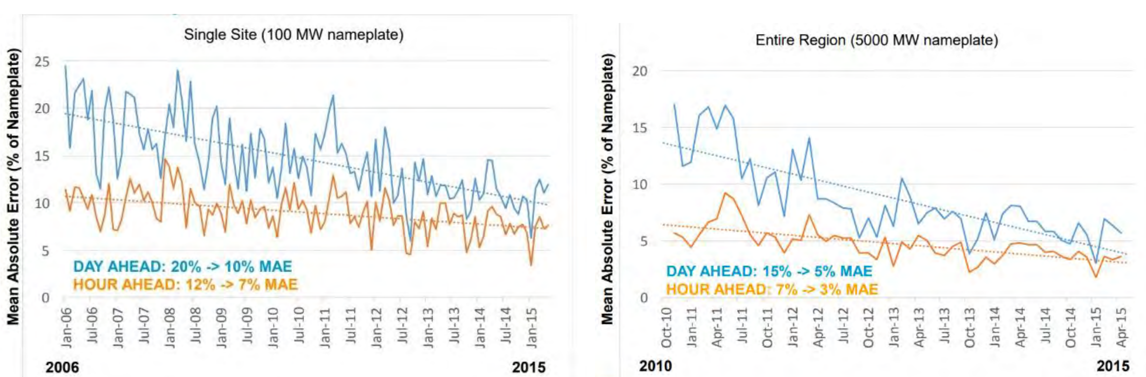
Forecasting error	*Description*	*Benchmark*
Normalized mean absolute error $NMAE = \frac{1}{N}\sum_{i=1}^{N}\frac{\lvert E_{actual,i}-E_{forecast,i}\rvert}{P_{nom}}$	Helps system operator understand the total error for a plant and plan reserves, as it is possible to sum the errors over all plants in the system.	Wind: 6–12 percent for a six-hour forecast, 10–20 percent for day-ahead forecasts
Mean absolute percentage error $MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{\lvert E_{actual,i}-E_{forecast,i}\rvert}{E_{actual,i}}$	Helps system operator concerned about system stability if renewable output drops below forecasted output.	Solar: 30 percent for hour-ahead forecast, 10 percent for four-hour ahead forecast
Root mean square error $RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(E_{forecast,i}-E_{actual,i}\right)^2}{N}}$	Measures the average accuracy of forecasts without considering the direction of the error; gives heavier weight to large errors. Helps illustrate the spread of errors, which increases confidence in the range of forecasts.	Wind: 7–19 percent for intermediate to short-term forecast; in China 11.7 percent for regional forecast, 16– 19 percent for single farm

Source: Foley et al. (2012); Inman at el. (2013); and Wang et al. (2011).

The accuracy of wind and solar forecasts increased considerably over the last decade, as technological developments improved the models and more historical data became available for analyses. Wind energy has reached impressive accuracy levels for day-ahead and hour-ahead forecasts. Errors for longer-term forecasts, such as a week ahead, remain relatively large.

Single-site wind forecasts errors fell 50 percent in a decade for both day-ahead and hour-ahead forecasts (Figure 3.3). Aggregating forecasts across a larger geographical area, to produce system level–wide forecasts, reduces errors even more.

FIGURE 3.3 Single-site and regional forecasting errors, 2006–15



Source: © Vaisala 2015. Used with the permission of Vaisala. Further permission required for reuse.

Forecast accuracy can be improved by (a) customizing methodology to account for local conditions and system operator needs and (b) using large amounts of historical data and high-performance computational resources. For example, the power curve of a VRE plant can be modeled using learning algorithms, regression methods, or curve fitting. The model will be "trained" with the available historical data, producing a fairly accurate output forecast, adaptable to changes in the power plant. BOX 3.1 presents an example from Denmark.

BOX 3.1 Using online measurements and historical data to improve the accuracy of wind forecasting in Denmark

Energinet, the Danish transmission system operator, forecasts future wind power generation based on two categories of information: input from an NWP model calculation and hourly online wind measurements. Denmark is divided into 25 areas for the purpose of the model calculation. The NWP calculates a forecast for wind power generation in each area based on input parameters such as wind speed, wind turbine generation data, installed capacity, and expected electricity prices. The forecast is calibrated using historical wind data and adjusted to reflect the fact that lower electricity prices reduce the wind power generation being offered for sale. As the delivery hour draws near, the forecast can be significantly improved using on-line wind speed measurements from the anemometers installed at about a third of Danish wind turbines. Using online wind speed measurements, the forecast can be updated at five-minute intervals in each of the 25 areas. The aim of the online measurements is to estimate the future error of the model calculation, in order to calculate a more accurate forecast.

Source: Energinet (2015).

4 | DEPLOYING A FORECASTING SYSTEM FOR VARIABLE RENEWABLE ENERGY

The first VRE forecasting system in United States was installed in in California in 2004 by the California's independent system operator (CAISO), primarily for wind energy. Since then several dozen system operators and a significant number of generators have deployed VRE forecasting systems.

Deploying a forecasting system in an existing management system requires careful planning and familiarity with the forecasting system architecture to be able to inform the most appropriate option for a power system. This section summarizes some of the key points of such systems from the viewpoint of the system operator. For a generator, the overall architecture will be similar, but the exact functions and interactions between systems might change.

BOX 4.1 Combining centralized and decentralized forecasting in India

In 2015, India proposed a framework on forecasting, scheduling, and imbalance handling for wind and solar at the interstate level (Cercind 2015). It stipulates that both generators and the concerned regional load dispatch centers issue wind and solar forecasts. The entities' forecasts have complementary objectives. The grid operator forecast is the basis for a secure grid operation including ancillary services requirements; the renewable energy generator forecast is the basis for scheduling.

The procedure for the framework on forecasting for VRE generating stations became active in 2017 (POSOCO 2017). It requires that solar and wind generators provide the system operator with the following information:

- Day-ahead available capacity, day-ahead forecast (based on own forecast or forecast by regional load dispatch centers), and day-ahead schedule, all at 15-minute intervals. On the day of actual generation, if any, the generator provides revisions of the availability and schedule.
- Real-time availability (at turbine/inverter level) and generation data (at substation level).
- Monthly data transfer to system operator (average winds speed and generation for wind plants at the turbine level and average solar irradiation and power generation for solar plants for all inverters, all at 15-minute intervals).

Action

A European company provides advanced weather forecasts services for more than 1,000 locations in India, including wind farms, large solar parks, and solar PV rooftops. It provides high-resolution data, with one-minute resolution for the next few hours and hourly resolution for up to a week for wind speed and direction at different height levels, solar irradiance at surface level, temperature, visibility, wind gusts, probabilistic forecasts, and other weather variables. The information, which is updated four times a day, is used to provide forecasting and scheduling services to solar and wind independent power producers in India.

Outcome

Integration of better VRE forecasting leads to better VRE management, which reduces fuel costs and improves system reliability, among other benefits.

Designing a Forecasting System

One of the design features of a forecasting system is whether the forecasting will be centralized (performed by the system operator) or decentralized (performed by plant operators) who feed the forecasts back to the dispatch center. Each method has benefits and challenges based on the type of information available.

The system operator requires a holistic view of the power system to ensure its safe operation, determine ancillary services and reserve margins, and so forth. A centralized forecasting system will result in more consistent (though not necessarily more accurate) results, because the same models and approaches will be used across the system. The system operator may also have access to information from a large number of plants across geographically dispersed locations that can help improve the forecast. A larger number of plants also results in scale economies on a per plant basis. However, a centralized system may have systematic biases that distort the forecast, either system-wide or for individual plants that do not conform precisely to the model's assumptions.

A decentralized forecasting system may be better able to model individual plant output, but it lacks the benefits of the centralized approach. Individual plant operators have more precise information about the availability and real-time generation of the plant. A decentralized approach also provides more freedom to innovate the models to improve accuracy or reduce computing needs or increase the local spatial resolution of the model (NERC 2010).

Centralized and decentralized forecasting are complementary, not mutually exclusive. In India, for example, both the regional load dispatch centers and the VRE generators are required to issue forecasts (BOX 4.1).

Basic Components of a Forecasting System

A forecasting system must convert the raw forecast data from various models into a flow of information useful to the system operator. The major components of a typical IT-based forecasting system include the following (Figure 4.1):

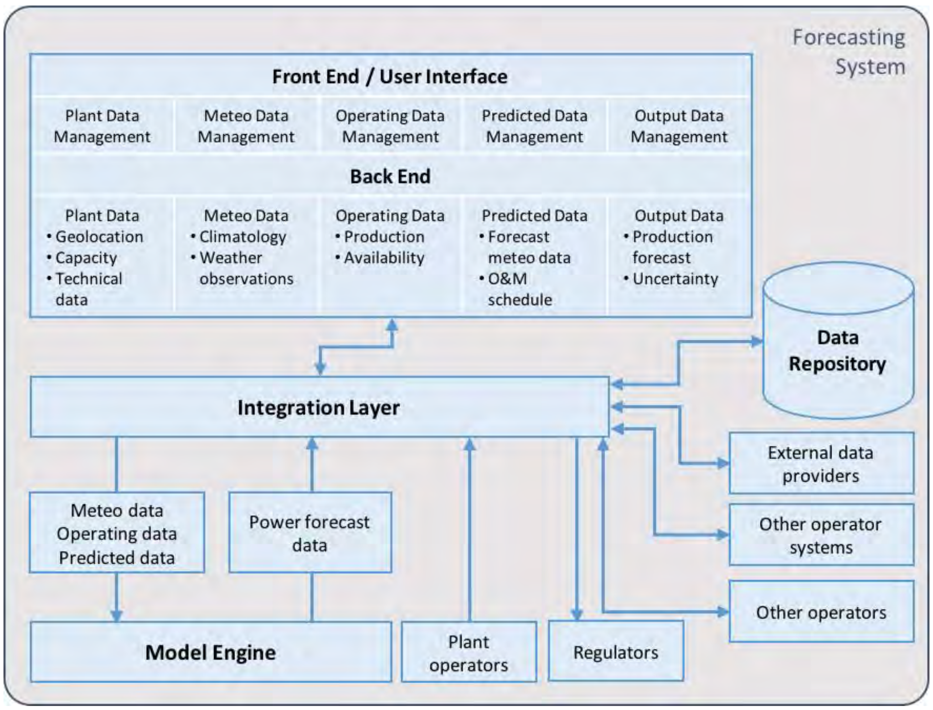
- front end/user interface (allows users to interact with the forecasting system)
- back end (connects components of a forecasting system)
- IT integration layer (enables communication within the forecasting system and with other systems)
- data repository (contains working data for the forecasting system)
- model engine (generates plant output forecasts based on the model).

To produce a forecast, the integration layer passes the forecast request and data from the back end to the model engine. Depending on the parameters of the request, the model engine executes with different time horizons, spatial resolution, or domains. The integration layer must also ensure that the engine receives all the data, correctly formatted, it needs to carry out the forecast. The integration layer receives the results of the fore end and updates other systems as necessary.

Front end. The front end provides a user interface for interacting with the forecasting system. It allows the user—in this case the grid or plant operator—to manage the system configuration; enter plant technical and geographical details; load meteorological observations and forecast data from external providers; enter upcoming O&M schedules; view the forecasted power output and uncertainty of the forecast; schedule the creation or retrieval of a forecast; and interact with other systems that rely on forecast output data, including Supervisory Control and Data Acquisition (SCADA)/Energy Management Systems (EMSs), dispatch, and market systems.

Back end. The most critical back end functions are system and data management. Ensuring that data are correct and available to other processes is essential to the functioning of the entire system. The back end also schedules and executes the processes involving data analysis and communicates with other components of the forecasting system.

FIGURE 4.1 Major components of a forecasting system



Integration layer. The integration layer enables connection of the forecasting system to other systems run by the operator or other parties. It therefore must be developed in a way that lends itself to easy extension and connection to other systems as other components evolve and requirements change. For example, it may be necessary to provide a standardized application programming interface to other systems and ways to transfer data to other systems automatically and on demand, through a file transfer protocol (FTP) portal, web services, or even email. The integration layer address requirements of several system stakeholders and is responsible for ensuring proper access control for all users of the data and to the forecasting system itself. Users of the integration layer include the following:

- the forecasting system operator, which uses the integration layer to run the system and to transfer data to and from the front and back ends, the repository, and the model engine
- plant operators, which feed technical, upcoming availability, and O&M data to inform the forecast
- regulators, which provide oversight
- external data providers, such as meteorological agencies, which provide meteorological data for the forecast
- other interconnected systems run by the operator, including SCADA/EMS

- other system operators, which rely on the forecasting system to provide data or forecasts from the operator.

***Data repository*.** The data repository serves as the central storage for all data needed by the system to make forecasts. Given the critical importance of the data, the different types and uses of data, and the size of the dataset, the repository must be flexible while remaining resilient to corruption and attack. Data include plant technical specifications; market data; weather data (forecast and observed); plant operating data (including production, wind speeds, and total insolation); and outputs (historical and forecast).

***Model engine*.** Given the size, complexity, and computing requirements of most models, the model engine is usually separated as a standalone modular component. Separation permits swapping the engine to allow the use of newer and more accurate models, more detailed resolution models, additional computing power rented from other providers, and other types of flexibility. For example, an external forecast from the model engine provided to the user through the front might be replaced by a tailored in-house model based on software like SPSS, with significantly different data and processing needs. BOX 4.2 shows an example from Australia.

BOX 4.2 Using wind and solar energy forecasting systems in Australia

The Australian Energy Market Operator (AEMO) manages both wholesale and retail electricity markets across eastern and southeastern Australia and oversees the vital system operations and security of Australia's national electricity market.

Action

Over the last decade, AEMO developed wind and solar energy forecasting systems, in response to the growth in VRE generation and the impact that growth was having on forecasting processes. The system aims to provide better forecasts that will drive improved efficiency of the national dispatch and pricing and permit better network stability and security management. Implementation of solar and wind forecasting had two broad objectives: facilitating the operation of the market through more accurate wind and solar generation forecasts and facilitating research to improve the quality and dimension of the forecast.

AEMO hosts the system and maintains its interface with existing market systems to give data access to the market and to individual wind farms. Data access is also given to researchers who sign a sub-licensing agreement and provide appropriate confidentiality arrangements.

The models produce forecasts from the following inputs:

- real-time SCADA measurements from wind farms
- Global weather forecasts from NWP models
- standing data from wind farms and solar power stations
- availability information provided by wind farms, including turbines under maintenance and upper MW limits on the wind farm
- additional information provided by the solar power station, including inverters under maintenance and upper MW limits on the solar farm.

Wind and solar generation forecasts are provided for all wind farms and solar power plants that produce at least 30MW of power for all forecasting time frames, as follows:

- 5-minute ahead dispatch

- 5-minute pre-dispatch: 5-minute resolution looking out one hour ahead, updated every 5 minutes
- pre-dispatch: 30-minute resolution up to 40 hours ahead
- short-term projected assessment of system adequacy: 30-minute resolution seven days ahead
- medium-term projected assessment of system adequacy: daily resolution two years ahead.

In 2016, AEMO implemented a solar forecasting system for small-scale (less than 100kW) solar installations. It uses a combination of statistical and physical methods and NWP-based models to produce aggregated regional solar generation forecasts for small-scale PV systems.

Source: AEMO (2017).

Data Requirements for Plant Production Forecasts

To increase the accuracy and completeness of the forecast, a typical forecasting system requires significant amounts of data on the status of plants, meteorological conditions, and O&M. Although the list provided in Table 4.1 is not comprehensive, it provides insight into the level of data required to develop an accurate power output forecast.

TABLE 4.1 Data requirements for forecasting production at a variable renewable energy plant

Indicator	*Required*	*Useful*
Plant data		
Geographical coordinates of all plant sites	✓	
Installed capacity (nominal power) of plants	✓	
Basic technical data on wind power plant turbines or PV units (rated power, hub height, rotor diameter, environmental specifications)		✓
Observed meteorological data (at least hourly time resolution)		
Air temperature at specified height, relative humidity at specified height, atmospheric pressure at surface		✓
Wind: Data from 50-meter mast and wind speed and direction at specified height		✓
Solar PV: Global horizontal irradiance or global tilted irradiance, whole sky-image		✓
Operating data (at least hourly time resolution)		
Power output of plant from SCADA and metering data	✓	
Installed capacity	✓	
Plant power availability (operating output range, by turbine or PV unit)		✓
Wind: Turbine data, including active power, temperature at nacelle level, wind speed measured by nacelle anemometer, wind direction measured by nacelle wind vane, and machine status		✓
Solar PV: Individual element data, including active power and temperature		✓
Historical data (at least three months at hourly resolution)		
Statistical method models: Detailed meteorological data and output	✓	
Upcoming data		
Meteorological forecast: Wind speed, wind direction, and precipitation	✓	
Meteorological forecast: Air pressure, temperature, humidity, cloud coverage, and radiance		✓
Scheduled plant reduction in output or downtime	✓	

SCADA/EMS and meteorological agency records capture most of the data required for forecasting. In a vertically unbundled marketplace, historical output data are likely available from the power market operator, which is required to pay operators for generated energy.

Sourcing a Forecasting System

Most countries have commercial VRE forecasting systems. Off-the shelf forecasting systems or systems for each component can be developed in-house or purchased commercially, as long as they are well integrated, through a comprehensive and flexible integration layer that allows interaction with all systems.

Off-the-shelf forecasting systems are bundled as a package. Rather than use them, many system operators prefer to use different suppliers for different components of the forecasting system, for cost, performance, or applicability reasons. An operator could, for example, purchase the front and back end from an existing SCADA vendor, contract with a storage provider for hardware and maintenance of the data repository, build a custom integration layer that interacts with both the new forecasting system and existing SCADA systems, and buy a forecasting as a service from a provider. Table 4.2 identifies the pros and cons of three major options.

TABLE 4.2 Pros and cons of three options for sourcing a forecasting system

System type	*Pros*	*Cons*	*Comments*
Self-developed system	Provides flexible, highly customizable, continuous improvement.	Takes time and qualified in-house personnel to develop; feature additions can be expensive].	Costs are driven primarily by personnel costs and the costs of acquiring commercial weather forecasts.
Commercial provider	Provides reliability, security economies of scale, and integration with existing systems.	Is expensive, lacks flexibility, takes time to set up.	Estimated cost includes license and system set-up only; costs for hardware, which can be significant, are not included.
Forecast as a service	Provides simple, flexible, worldwide availability, at low cost.	Black box, proprietary data are sent off-site for processing and retention.	Discounts may be available for more plants. Costs are extrapolated from European experience.

***In-house development*.** Self-developed systems offer an operator the most flexibility, but they may require a significant amount of qualified in-house technical skill. Depending on the level of sophistication of the system and available existing resources, system costs may vary significantly—and the operator bears the cost of all maintenance and feature additions.

If the operator already has a significant investment in information and operational technology—for example, a SCADA system with integrated EMS billing, planning, and management functions—adding an additional module for forecasting may not be very challenging, as many of the data required for an effective forecasting system are already collected in these systems and can be channeled to the forecasting system. Adding a forecasting module may therefore be as simple as integrating some publicly available models and ensuring that data are available to support the models.

***Commercial systems*.** Commercial systems can be sourced from companies that also offer EMS or BMS software. Many operators already have some level of SCADA/EMS or BMS active, which they purchase from a company that specializes in such hardware and software. These companies sometimes offer forecasting as part of a system package bundled with production EMS software. For example, to conduct transactions on a day-ahead market, energy trading software may offer a module to help forecast production.

The costs of such systems are clearly defined compared with self-developed systems, but licensing costs are relatively high and implementation costs may be considerable. Ongoing licensing and operational costs can scale linearly with every additional turbine and PV unit; if the system is already in use for other purposes, add-ons may be free or relatively inexpensive.

For companies that require on-premise systems for security or reliability reasons, commercial systems offer the ability to run on hardware at the operator's site. Most commercial providers also offer installation and ongoing maintenance contracts at an additional fee, increasing the cost certainty for a system operator. Customizability is limited, however, and costly if offered at all.

Various vendors have modules or systems that provide VRE power production estimates. Some offer on-premise modules, others carry out model calculations offsite in a vendor-owned computing facility. Some of these systems also provide other types of EMS facilities. Many vendors offer both wind and solar energy forecasting; others offer only wind forecasting.

Forecast as a service. A large and growing number of meteorological data providers and other companies offer plant and system operators the option to send required data to them and receive the forecast production data back. In a forecast-as-a-service model, the provider works with the operator to define the kinds of forecast options needed and determine what data are required from the operator and at what time resolution. The operator-provided data are then run through a sophisticated and constantly improving model at the provider's site to generate the required forecast data. The forecast provider can also either generate its own meteorological forecast or acquire it for a fee from another company as an input to its model. The estimated power production forecast is then sent back to the operator and used to inform the rest of the operator's system management tools. Data transfers happen either manually through a portal that can be triggered on-demand by the operator or through automated transfers using standardized programming interfaces.

Such services tend to charge by power plant per year, meaning that costs scale not with individual wind turbine or PV units but rather with the number of plants providing energy. Higher time resolutions or increased complexity can drive up operational costs. Start-up costs are also usually needed to integrate the data into an existing EMS. While the operator is likely to receive even better forecasts as the provider improves the model, customization may be difficult for forecast-as-a-service providers, because the forecast provider is banking on scale efficiencies in the development of the model and provision of service.

Different countries have taken different approaches to forecasting. In the Republic of North Macedonia, a commercial provider carries out the VRE forecasting for the system operator as a service (BOX 4.3). In South Africa generators contract a forecasting service directly to provide forecasts to the plant operator (BOX 4.4).

BOX 4.3 Using a commercial provider to forecast variable renewable energy in the Republic of North Macedonia

The Republic of North Macedonia has more than 100MW of wind, solar, and small-hydro (run-of-the-river) capacity, distributed in more than 120 power plants across the country (peak demand in Macedonia in 2015 was 1,440MW)—and the government is taking steps to increase the share of renewable energy sources in the country's energy mix. Renewable energy producers that obtain the status of preferential producers are entitled to certain benefits, including priority.

The transmission system operator (MEPSO) is the single buyer of renewable energy from preferential producers, which it sells to suppliers and traders. MEPSO also prepares and publishes final forecasts for electricity generation Each renewable energy producer submits generation schedules and is financially responsible for deviations (Energy Community 2017).

Action

Since 2015, MEPSO has used short-term power forecast as a service (day ahead and week ahead) for daily improvement of forecasting accuracy.

Outcome

MEPSO uses a cloud-based graphical interface to monitor renewable output signals to ensure grid stability in the network and optimal balancing throughout the countries. Standardized renewable energy forecasting contributes to the smooth and cost-efficient operation of the electric power system.

BOX 4.4 Using third-party forecasting services in South Africa

By law, South Africa's renewable energy generators are required to submit to the national transmission system operator (Eskom) the following information:

- Day-ahead MW forecasts, with hourly resolution, and the available MW for a week. Forecasts are submitted daily before 10:00 a.m.
- Intra-day forecast MW, with hourly resolution, and available MW. Forecasts are submitted 10–20 minutes before each hour.

Action

Since 2014 a solar PV monitoring system provider has provided forecasting services to individual renewable generation plants for hour-, day-, and week-ahead time horizons. In real time, the NWP and monitored power plant output signal feed in a customized statistical model of each plant to forecast power, providing nowcasting services that yield a more accurate forecast for the next six hours, updated every hour. This service enables power plant owners to use real-time data from their monitoring systems to update their power generation forecast hourly, complying with the requirement in the South African grid code (Grid Connection Code for Renewable Energy Version 2.9).

Outcome

Renewable power producers can provide hourly intra-day and day-ahead power forecasts to inform Eskom of the upcoming power injection to the grid.

Companies in Australia, Demark, Germany, Ireland, Spain, and other countries provide these services. Most providers offer coverage only in a handful of countries (Australia, some countries in Europe, and the United States), because of their familiarity with meteorological forecasts in those countries.

5 | CONCLUSIONS

Wind and solar forecasting are cost-effective operational solutions to manage the variability and uncertainty of VRE generation. An VRE forecasting system with advanced functionalities can blend physical and statistical methods and use inputs from satellites, radar systems, ground-based weather stations, and sensors. VRE forecasting at different time scales informs system operations and provides an important decision support foundation for running the grid with renewable resources. Installing and using a state-of-the-art forecast system provides benefits to grid operators, VRE generators, and power systems at large.

Wind energy forecasting is a well-established industry. Several commercial systems and services are in the market, and much research has been conducted. Solar power forecasting is still relatively new, especially for ultra-short-term forecasting, but it is showing promising results, thanks to technological developments.

Several factors affect forecast performance and accuracy, including the siting of the plant, the forecast time horizon, local weather conditions, the geographic scope, data availability, and data quality. Weather forecasting technological developments and the growing availability of historical data have helped improve models, increasing the accuracy of VRE forecasting. Competition among commercial providers has driven improvements in VRE forecasting.

Forecasting is an effective and relatively inexpensive tool to increase the penetration of renewables in an electrical system. It can be carried out centrally (by the system operator) or in a decentralized way (by plant operators). The two methods are complementary; using them in parallel yields the greatest benefits, as it takes advantage of the different information provided by the system operator and plant operator.

Advanced VRE forecasting systems can be sourced in various ways. For maximum flexibility, operators can develop their forecasting systems in house. Alternatively, operators can purchase forecasting as additional software modules of an existing EMS or as a service.

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