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ADVANCED FORECASTING OF VARIABLE RENEWABLE POWER GENERATION

INNOVATION LANDSCAPE BRIEF

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ABOUT IRENA

The International Renewable Energy Agency (IRENA) is an intergovernmental organisation that supports countries in their transition to a sustainable energy future and serves as the principal platform for international co-operation, a centre of excellence, and a repository of policy, technology, resource and financial knowledge on renewable energy. IRENA promotes the widespread adoption and sustainable use of all forms of renewable energy, including bioenergy, geothermal, hydropower, ocean, solar and wind energy, in the pursuit of sustainable development, energy access, energy security and low-carbon economic growth and prosperity. **www.irena.org**

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1 BENEFITS

Accurate generation forecasts for solar and wind power – short term and long term, centralised and decentralised – are valuable to system operators and renewable generators.

Short-term forecasting	Benefit	Long-term forecasting
Electricity trading in spot markets	GENERATORS BENEFIT	Renewables plant placement
System stability	SYSTEM OPERATORS BENEFIT	System planning

SHORT-TERM FORECASTING → LONG-TERM FORECASTING

2 KEY ENABLING FACTORS

- Regulatory incentives for accurate variable renewable energy (VRE) forecasting
- Open source systems for weather data collection and sharing
- Advanced meteorological devices

3 SNAPSHOT

- → Australia invests USD 5.6 million in advanced wind and solar forecasting to improve decisions made on spot markets.
- → The UK system operator uses artificial intelligence to better predict renewable generation.
- → A study from the California Energy Commission indicates potential savings of USD 2 million yearly with improved solar and load forecasting.

WHAT IS ADVANCED GENERATION FORECASTING?

Meteorological technology captures real-time, site-specific weather data. Algorithms produce advanced forecasts for solar and wind output.

ADVANCED FORECASTING OF VARIABLE RENEWABLE POWER GENERATION

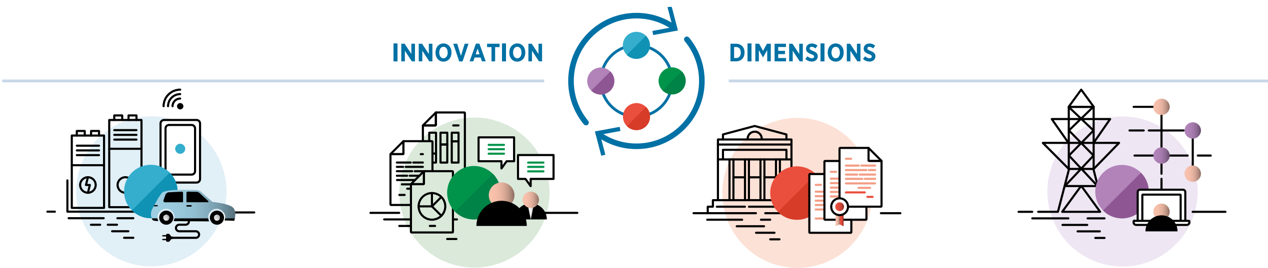
Improved weather forecasts allow accurate estimates of the amounts of solar and wind electricity likely to be available in specific time frames.

ABOUT THIS BRIEF

This brief forms part of the IRENA project "Innovation landscape for a renewable-powered future", which maps the relevant innovations, identifies the synergies and formulates solutions for integrating high shares of variable renewable energy (VRE) into power systems.

The synthesis report, "*Innovation landscape for a renewable-powered future: Solutions to integrate variable renewables*" (IRENA, 2019a), illustrates the need for synergies between different innovations to create actual solutions. Solutions to drive the uptake of solar and wind power span four broad dimensions of innovation: enabling technologies, business models, market design and system operation.

Along with the synthesis report, the project includes a series of briefs, each covering one of 30 key innovations identified across those four dimensions. The 30 innovations are listed in the figure below.



ENABLING TECHNOLOGIES

1 Utility scale batteries
2 Behind-the-meter batteries

3 Electric-vehicle smart charging
4 Renewable power-to-heat
5 Renewable power-to-hydrogen

6 Internet of Things
7 Artificial intelligence and big data
8 Blockchain

9 Renewable mini-grids
10 Supergrids

11 Flexibility in conventional power plants

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18 Increasing space granularity in electricity markets
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22 Time-of-use tariffs
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SYSTEM OPERATION

25 Future role of distribution system operators
26 Co-operation between transmission and distribution system operators

27 Advanced forecasting of variable renewable power generation
28 Innovative operation of pumped hydropower storage

29 Virtual power lines
30 Dynamic line rating

This brief provides an overview of the concept of advanced weather forecasting and its importance for VRE integration into power systems. Emphasis is placed on the contribution of both short- and long-term weather forecasting for renewable generators and power system operators. Key enablers required for its development and implementation are presented, together with examples of ongoing initiatives.

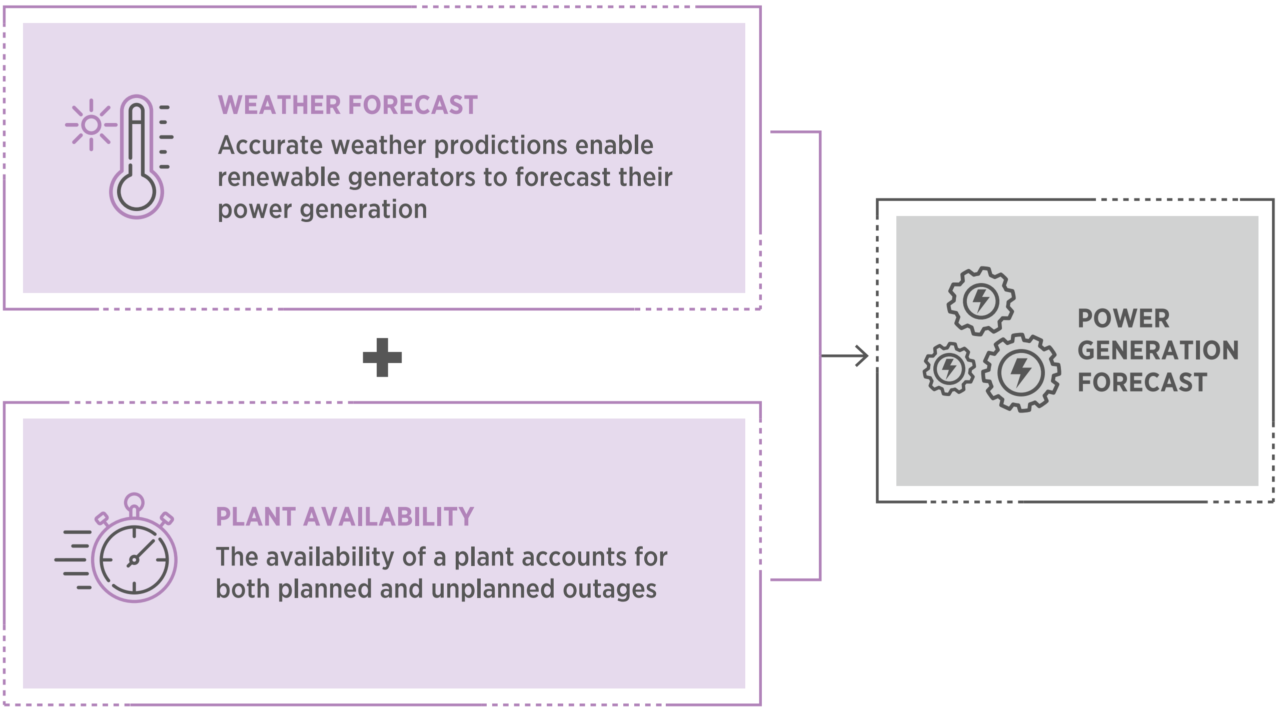
The brief is structured as follows:

I. DESCRIPTION

Accurate weather forecasting is crucial for integrating wind and solar power generating resources into the grid, especially at high penetration levels. It is a crucial, cost-effective tool available to both renewable energy generators and system operators (NREL, 2016).

For weather-dependent renewable generators, like solar and wind power plants, the most critical scheduling input comes from weather forecasting data. A power generation forecast is a combination of plant availability and weather forecasts for the location, as illustrated in Figure 1.

Figure 1 Weather and power generation forecast



Advanced weather forecasting methods take advantage of advances in digital technologies, such as artificial intelligence (AI) and big data, to analyse live and historical weather data and make predictions. In fact, advanced weather forecasting is one of the main applications of AI in facilitating and improving VRE integration (for more information see *Innovation landscape brief: Artificial Intelligence and Big Dat*a [IRENA, 2019b]). Driven by an increase in computing power and improvement in algorithms, power generation forecasts have become more accurate. In a similar vein, thanks to the increasing use of AI fuelled by big data, time granularity for short-term predictions has increased as well. These factors can greatly contribute to the integration of renewable power into the grid (Bullis, 2014).

Improving VRE generation forecasts on short-term and long-term timescales engenders a diverse set of benefits for various stakeholders in the power sector. At short timescales, accurate VRE generation forecasting can help asset owners and market players to better bid in the electricity markets, where applicable. Bids based on more accurate forecasts would reduce the risk of incurring penalties for imbalances (*i.e.* for not complying with the generation offered in the bid). For power system operators, accurate short-term VRE generation forecasting can improve unit commitment (operation scheduling of the generating units) and operational planning, increase dispatch efficiency, reduce reliability issues and, therefore, minimise the amount of operating reserves needed in the system.

Over longer timescales (*e.g.* over days or seasons), improved VRE generation forecasting based on accurate weather forecasting brings significant benefits to system operators, especially when planning for extreme weather events. By contributing to the allocation of appropriate balancing reserves, long-term weather forecasting assists in ensuring safe and reliable system operations. It can also help in better planning the long-term expansion of the system, both generation and network transmission capacity, needed to efficiently meet future demand.

Every energy forecast invariably starts with numerical weather prediction (NWP) models, which are the accepted baseline predictions being tuned and run by large and mostly government-funded organisations. NWP methods take weather data, such as temperature, pressure, humidity, as inputs to simulate weather conditions in the future using physical and mathematical laws.

These simulated weather predictions can then be converted to corresponding energy production from wind and solar resources. NWPs are normally used for 15-days-ahead forecasting. However, these models are not accurate over short timescales (less than a few hours). Statistical approaches are also commonly used and are based purely on historical learnings. Solar irradiation forecasts also employ sky imagers (digital cameras that produce high-quality sky images) and satellite imaging (data from networks of geostationary satellites) to track and predict cloud formations at different timescales. Hybrid models use two or more techniques in conjunction to minimise the forecasting error. These hybrid methods have produced the best forecasting results when compared with individual statistical and machine learning techniques for all types of time horizon (Akhter *et al.*, 2019).

Compared with large-scale dispatchable plants, forecasts for distributed solar photovoltaic (PV) generation are more difficult to produce because of the relatively small size and large number of solar PV sites. Such forecasts are most accurate when near-real-time power generation data and detailed static data (*e.g.* location, hardware information, panel orientation) are available for all connected systems (NREL, 2016).

For example, 11 Renewable Energy Management Centres (REMCs) are being set up in India. The REMCs are equipped with AI-based renewable energy forecasting and scheduling tools at the regional level and provide greater visualisation and enhanced situational awareness to the grid operators. In total, 55 gigawatts (GW) of renewable power (solar and wind) is being monitored through the 11 REMCs (Asian Power, 2020). In Germany, the power generation forecasts for transmission system operators (TSOs) and distribution system operators (DSOs) are calibrated and evaluated against estimations of the solar power production on a postal code level. Forecasts of aggregated distributed solar PV production are developed and validated by upscaling the output from a subset of representative solar PV sites. The process is similar in California, where information about all solar PV systems in the state is recorded and then combined with high-resolution solar irradiance values and weather predictions to forecast power output for the entire state. This bottom-up approach is employed by the California Independent System Operator (CAISO) to predict the total contribution of behind-the-meter solar plants to its grid.

Table 1 lists the methods used for power generation forecasting at different time horizons, as well as the key applications of these forecasts in the power sector. The forecasting accuracy decreases with the increase of forecast time horizon, even for the same forecasting technique. Thus, the selection of a proper time horizon before designing a forecasting model is key to maintaining the accuracy of forecasting at an acceptable level (Akhter *et al.*, 2019).

Table 1 Generation forecast methods and applications

	Time Horizon	Methods	Key Applications
Power Generation Forecast	5–60 min ahead of real time	Statistical[a], persistence[b]	Regulation, real-time dispatch, trading, market clearing
	1–6 hours ahead of real time	Blend of statistical and NWP models	Scheduling, load following, congestion management
	Day(s) ahead of real time	NWP with corrections for systematic biases[c]	Scheduling, reserve requirement, trading, congestion management
	Week(s), seasonal, 1 year or more ahead of real time	Climatological forecasts, NWP	Resource investment planning (generation, network), contingency analysis, maintenance planning, operation management

Source: Based on NREL (2016).

Note: min = minutes; NWP = numerical weather prediction.

[a]Use historic and real-time generation data to provide statistical corrections to predictions of the NWP models.

[b]Simple statistical methods that assume that the current generation will remain unchanged in the near future. They are used as benchmarks to evaluate other advanced forecasting models.

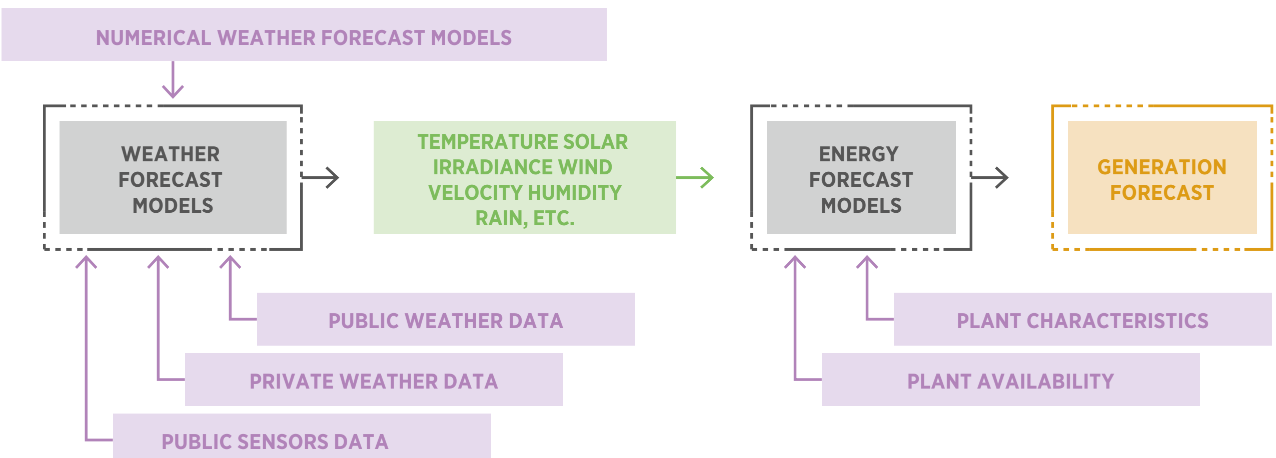
[c]Errors inherent in the measurement process.

Very short-term forecasting (from seconds to 1 hour) is useful for real-time electricity dispatch, optimal reserves, and smoothing power production of solar and wind. Short-term forecasting (from 1 hour to 24 hours) is useful to increase the stability of the grid. Medium-term forecasting (one week to one month) maintains the power system planning and maintenance schedule by predicting the available electric power in the near future.

Long-term forecasting (one month to one year) helps transmission and distribution authorities in electricity generation planning, in addition to energy bidding and security operations (Akhter *et al.*, 2019).

Complex modelling is required to account for all the variables that affect local weather. Figure 2 illustrates, in a simplified way, the data needed and the methodology applied for VRE power plants' generation forecasts.

Figure 2 From weather to power generation forecast



II. CONTRIBUTION TO POWER SECTOR TRANSFORMATION

Accurate weather forecasts and very short-term to long-term forecasting are key for effectively integrating VRE generation into the grid and bring valuable contributions for both renewable generators and system operators. Figure 3 summarises the benefits of short-term forecasting (defined here as minutes to one day ahead) and long-term forecasting (weeks to one year ahead).

System operators usually use centralised forecasting of renewable generation, widely considered a best-practice approach for a cost-effective dispatch.

Centralised forecasts provide systemwide forecasts for all VRE generators within a balancing area. Decentralised forecasts, administered by individual VRE asset operators, provide plant-level information to help inform system operators of potential transmission congestion due to a single plant's output, as well as help position the plant's bids in the forward or short-term markets (NREL, 2016). System operators can also benefit from decentralised forecasting by aggregating these data and using them for both short- and long-term operational procedures.

Figure 3 Benefits of weather forecasting to system operators and renewable generators

BENEFITS OF WEATHER FORECASTING	CENTRALISED FORECASTING / DECENTRALISED FORECASTING: For system operators	DECENTRALISED FORECASTING: For renewable generators
Short-term forecasting	Improved network management and system balancing	Advantages for intraday and day-ahead electricity market trading
Long-term forecasting	Reserve planning and operation management	Efficient placement of renewable plants
	Planning for extreme weather events	

Contributions of short-term weather forecasting

Improved network management and system balancing

Short-term centralised forecasting is useful for applications related to system operations, such as real-time dispatch, market clearing and load following. Furthermore, accurate weather forecasting can also provide advantages in short-term electricity trading and system balancing. This leads to improved grid reliability and enables the efficient use of renewable energy resources.

Better weather forecasting using AI supercomputers that synthesise data from various sources, including historical weather data, real-time measurement of local weather conditions, satellites and sensors, is expected to lead to more accurate estimations of generation ramping requirements. More accurate estimations will be useful in improving grid reliability.

Day-ahead forecasts provide hourly power values used in the scheduling process to help avoid costs and inefficiencies due to unnecessary starts and stops of thermal generators. Intraday forecasts typically provide power values with frequent time steps (*i.e.*, every 10 minutes) up to a few hours ahead of real time. They are used in real-time dispatch and market-clearing decisions.

VRE generation forecasts can be, for example, integrated with load forecasting to produce net load forecasts, which improve the visibility of demand-side variations. VRE forecasts can be also integrated by system operators into a power flow module, which is a part of energy management systems, to detect voltage and congestion problems with a certain probability threshold.

Advantages for intraday and day-ahead electricity market trading

Short-term decentralised forecasts engender benefits for generators, especially if there is a functioning electricity market in place, and help renewable generators define their bidding strategies.

Accurate weather forecasts can enable renewable power generators to better estimate the generation and bid accordingly in intraday or day-ahead markets, reducing penalties imposed for deviations between actual and scheduled power generation. By using a more advanced forecasting solution with NWP models, renewable energy forecasts can be predicted closer to actual generation time. Statistical methods using AI models consider project-specific data along with nearby weather conditions for more accurate short-term forecasts. System operators in the United States, such as the Midcontinent Independent System Operator and Electric Reliability Council of Texas, combine short-term dispatch with very short-term forecasts (within 10 minutes of the actual flow of power), which allows wind power plants to be fully integrated into real-time intraday markets (Orwig *et al.*, 2015).

Contributions of long-term weather forecasting

Reserve planning and operation management

Long-term weather forecasts are valuable for system operators in applications such as reserve planning and operation management. Such forecasts may further assist generators and system operators in investment planning for, respectively, power plant construction and system expansion.

Planning for extreme weather events

Long-term weather forecasts can be used by system operators to predict extreme weather events and better plan and prepare for such occasions. For instance, the North Atlantic Oscillations, which are seasonal weather phenomena over the North Atlantic and Europe caused by pressure differentials, can cause as much as a 1 020% variation in wind and solar generation (Jerez *et al.*, 2013). Long-term weather forecasts for such weather events can thus improve the resilience of the system, helping system operators in planning for alternative resources to ensure the security of supply.

Efficient placement of renewable plants

Long-term decentralised weather forecasts can help in the generation expansion of the system by identifying the best locations for the construction of new renewable power plants. For example, turbine placement in the wind industry is an important parameter affecting power generation. Major factors for appropriate turbine placement include wind speed, wind turbulence, wind direction, space and ecological considerations. Solar irradiation, also location specific, is crucial for solar PV projects.

Other important parameters are the zenith angle and the orientation of the PV panel. Advanced weather forecasting tools can be used for the identification of optimal sites for wind turbine and solar PV installations to improve generation outputs and reduce maintenance costs. Supercomputers can be used to analyse petabytes of structured and unstructured data – such as weather reports, tidal phases, geospatial and sensor data, satellite images, deforestation maps, and weather modelling research – to identify the optimal location of wind turbines (IBM, 2011).

Potential impact on power sector transformation

Several studies have explored the impact and implications of advanced forecasting for utilities, system operators and VRE generators:

- The impact of improvement in solar power forecasting was analysed in one study by evaluating the operations of the entire power system for four scenarios that represented four forecast improvement levels: 25%, 50%, 75% and 100% (perfect forecast). **The study showed that electricity generation from conventional sources (gas and oil generators) decreases with solar power forecasting improvement** (Martinez-Anido *et al*., 2016).

  Coal, gas combined-cycle, and gas and oil steam turbine generators are committed in the day-ahead run, while gas and oil turbines and internal combustion generators are committed in the real-time run. Table 2 shows, for different solar penetration levels, the impact of forecast improvement on the overall system generation mix. **Day-ahead operation can be better planned, and faster generators committed in real time can be used less, when solar power uncertainty decreases**.

Table 2 Impact of solar power forecasting improvement on power generation

Solar Penetration (%)	4.5				9.0				13.5				18.0			
Forecast Improvement (%)	25	50	75	100	25	50	75	100	25	50	75	100	25	50	75	100
Coal (%change)	0.0	0.0	0.0	0.1	0.1	0.2	0.2	0.3	0.1	0.3	0.4	0.5	0.2	0.4	0.4	0.4
Gas CC (%change)	0.0	0.2	0.1	0.1	0.1	0.1	0.2	0.3	0.3	0.7	0.9	1.1	0.5	0.9	1.4	1.8
Gas and Oil ST (%change)	-0.1	-1.4	-0.8	-0.8	0.6	1.2	0.5	0.0	-1.3	-2.8	-3.9	-4.8	-1.9	-3.5	-5.3	-5.5
Gas and Oil GT & IC (%change)	-0.8	-1.8	-1.9	-1.7	-4.5	-7.5	-8.6	-10.2	-3.9	-8.8	-12.1	-13.7	-5.1	-10.5	-14.3	-17.5

Source: Martinez-Anido et al. (2016).
Note: CC = combined-cycle; ST = steam turbine ; GT = gas and oil turbine; IC = internal combustion;.

The study shows also a **considerable decrease in solar power curtailment** with the improved forecast. The results of the study are shown in Table 3.

Table 3 Impact of solar power forecasting improvement on solar power curtailment

Impact (% change)	**Solar penetration (%)**		
Forecast Improvement (%)	9.0	13.5	18.0
25	-2.3	-1.2	-1.5
50	-4.0	-2.3	-2.7
75	-5.2	-3.5	-3.5
100	-5.4	-4.2	-3.8

Source: Martinez-Anido *et al.* (2016).

The same study found that the **impact of solar forecasting improvements** on solar curtailment and electricity generation, including ramping, starts and shutdowns on fossil fuel generators, results in **lower operational costs for the system**, as shown in Table 4.

Table 4 Cost savings from solar power forecasting improvement per unit of solar power generation

Forecasting improvement cost savings ($/MWh)	**Solar penetration (%)**			
Forecast Improvement (%)	4.5	9.0	13.5	18.0
25	0.11	0.33	0.39	0.50
50	0.29	0.62	0.77	0.95
75	0.30	0.74	1.03	1.25
100	0.32	0.82	1.13	1.42

Source: Martinez-Anido et al. (2016).
Note: MWh = megawatt-hours.

- National Grid, the TSO in the United Kingdom, is using AI and machine learning to help predict solar and wind generation. National Grid announced that its **new AI prediction models have improved solar forecasting by one-third**. The new system combines information, including temperature data, solar irradiation data, and historic weather data, to reach an output generation figure, which is then tested against 80 weather forecasts to give an energy generation forecast (Cuff, 2019).

- A study by the **California Energy Commission** evaluates the impact of improvement in solar and load forecasting on system operation in California (California Energy Commission, 2019). Solar forecasting includes forecasting for individual utility-scale resources and aggregated behind-the-meter resources, which total nearly 6 GW. Possible improvements to the solar forecasts include incorporating age-related degradation; improving inverter modelling, incorporating ever-changing amounts of solar capacity; and handling real-world performance issues, such as soiling, system outages and shading.

  However, the impact of behind-the-meter solar PV is not considered in forecasting loads in California. The study extended the existing load forecasting models to capture the influence of behind-the-meter solar PV and predict an increasingly volatile load. The results showed that **improvements in solar and net load forecasting methods can provide positive financial impacts in the scheduling and procurement of electricity** in the wholesale electric market within California. The results indicate that potential **savings of approximately USD 2 million per year** can be made, based on an average annual CAISO load of 26 GW and an average regulation cost of USD 9 per megawatt-hour. In addition to financial savings from operation, emission savings should result from the reduction in the need for spinning reserves (California Energy Commission, 2019).

- A study conducted for the California Independent System Operator (CASIO) shows that **improved short-term wind forecasting** in the CAISO market can **result in annual total cost savings**[1] **between USD 5 million and USD 146 million**, depending on the scenario, as shown in Table 5 (Hodge *et al.*, 2015). In the low wind scenario, available wind capacity amounts to 7 299 megawatts (MW), and in the high wind scenario, 11 109 MW of available wind capacity is expected. The time-based variability in the wind speed determines the instantaneous penetration level and the degree to which the forecasting accuracy influences the actual dispatch of generation.

Table 5 Total cost savings from improved wind power forecasting

Wind Scenario	Forecast improvement	Annual Savings (USD)
Low	10% uniform improvement	5 050 000
High		25 100 000
Low	25% uniform improvement	14 800 000
High		62 900 000
Low	50% uniform improvement	34 700 000
High		146 000 000

Source: Based on Hodge, *et al.* (2015).

1 *Capacity reserve, frequency regulation reserve and production cost savings.*

III. KEY FACTORS TO ENABLE DEPLOYMENT

A regulatory environment incentivising accurate VRE power generation forecasting

To enhance the operation of a power system with significant VRE shares, the regulatory and electricity market arrangements need to increase time granularity; in other words, the dispatch and scheduling time interval, the pricing of market time units, financial settlement periods, and the time span between gate closure and the real-time delivery of power should be reduced (for more infomration see *Innovation landscape brief: Increasing time granularity in electricity markets* [IRENA, 2019c]).

In this way, advanced weather forecasting methods, by delivering granular results and data closer to real time, become very important for VRE power generation. For instance, the Electric Reliability Council of Texas has reduced the dispatch time intervals from 15 minutes to 5 minutes, allowing updates in generation schedules until 10 minutes before the actual power dispatch. This change in rule has incentivised the use of better weather and generation forecasting methods and has resulted in reduction of wind curtailment due to better accuracy in generation forecasts 5 minutes before the actual generation, compared with the previous 15 minutes (Bridge to India, 2017).

Simultaneously, VRE generators and system operators must be incentivised to produce accurate generation forecasts at different timescales (*i.e.* week ahead, day ahead, intraday), providing the same time granularity as that used in the electricity markets. Accurate forecasts engender different benefits to generators and system operators. For this reason, two types of forecast are needed: centralised forecasting for system operators to maintain overall reliability; and decentralised forecasting for VRE generators, enabling them to revise their schedules and dispatch instructions. System operators can also benefit from the decentralised forecasting of VRE generators if communication between these stakeholders is established and automatised. Penalties for significant deviations in generation forecasts, compared with actual generation, can be implemented to incentivise improving the accuracy of decentralised forecasts.

Open source systems for weather data collection and sharing

Advances in digital technologies and data science, such as AI and big data – including predictive analytics and machine learning algorithms – can improve weather forecasting. However, these algorithms require large numbers of datasets to make accurate predictions. Therefore, open sourcing weather data collected by the weather monitoring stations of VRE generators, national meteorological institutes, and information and communication technology developers can foster rapid advances in data analytical techniques and consequently in weather forecasting.

For weather data collection, a network of weather stations at national or regional level can be deployed to collect and store long-term meteorological data, which can be used to characterise renewable energy resources. The Institute for Environmental Research and Sustainable Development, for example, operates such a network of automated weather stations across Greece. As of December 2016, 335 weather stations were operational and providing real-time data at 10-minute time intervals. These weather data are used by power system operators and private VRE generators, along with other industries, to plan and forecast both the load and the generation from various power generating resources.

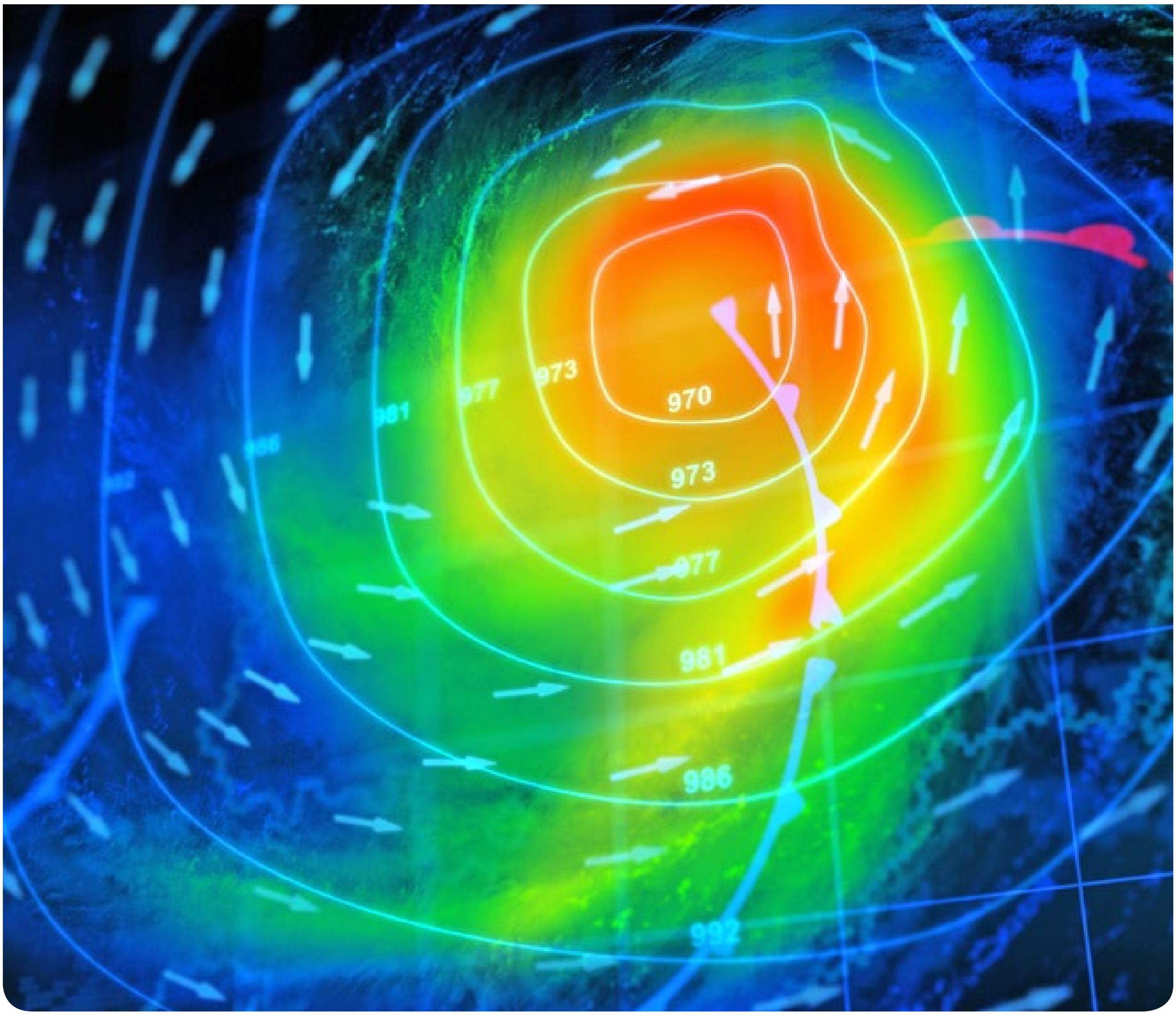
For the last 30 years, the Joint Research Centre has produced a dataset (known as EMHIRES) of wind energy production by the hour at the national, regional and local levels across the European Union; these data can be fed into advanced weather forecasting models for more accurate wind power generation forecasts to help policy makers devise better energy frameworks (European Commission, 2016).

At large power plants, meter data are typically available in near real time, and site metadata are generally known. For smaller distribution connected plants, dedicated meter data are usually available and recorded but are often not telemetered in real time, nor systematically used for system operation procedures.

Advanced meteorological devices

Other weather forecasting tools and models that are being experimented with include the use of advanced cloud-imaging technology; sky-facing cameras to track cloud movements; and sensors installed on turbines to monitor wind speed, temperature and direction. Using such advanced meteorological devices, which are connected to the Internet, may help in gathering information of real-time, site-specific weather conditions (for more information on Internet-connected devices, see *Innovation Landscape Brief: Internet of Things* [IRENA, 2019d]).

However, the impact of these instruments is still being investigated, and the technologies remain relatively expensive. Advanced ultrasonic sensors using ultrasound are being trialled to measure horizontal wind speed and direction. Sky cameras are also being tested to study cloud coverage, ultraviolet index, cloud movement, cloud heights, sky polarisation and wind speed at cloud heights. Automated weather stations attached to solar panels or wind turbines to report real-time information are also being developed. These weather stations contain data loggers and meteorological sensors that collect and save weather data for later applications.



IV. CURRENT CONTEXT AND ONGOING INITIATIVES

Short-term VRE generation forecasting solutions in Australia

The Australian Renewable Energy Agency (ARENA) awarded funding of some USD 5.6 million (AUD 9.4 million) to 11 projects to trial short-term forecasting at large-scale wind and solar farms across Australia. The trial covers at least 45% of the National Electricity Market's registered wind and solar capacity, which collectively provides a total of 3.5 GW of renewable electricity generation (ARENA, 2019).

The funding is part of ARENA's Advancing Renewables Program, and part of the study will focus on improving the Australian Wind Energy Forecasting System's 5-minute forecast. This solution will allow ARENA to more accurately forecast wind generation, reduce wind generators' dispatch uncertainty and improve system stability by balancing the energy supply and demand in the market.

The solution involves applying advanced data science techniques, including deep learning, to deliver greater accuracy in energy forecasts, both for specific sites and technologies and for the system as a whole.

These are applied to high-resolution wind turbine data from the supervisory control and data acquisition system, granular short-term hyperlocal weather forecasts and meteorological data. The solution will couple physical and statistical models with an industry-best 1 square kilometre (km^2) precision, compared with traditional global weather forecasts, which operate at coarser temporal resolution and 16 km^2 spatial resolution (Utopus Insights, 2019).

Sun4Cast Solar Generation Forecasting System in United States

The Sun4Cast solar generation forecasting system combines various forecasting technologies, covering a variety of temporal and spatial scales, to predict local solar irradiance. Forecasts from multiple NWP models are combined via the Dynamic Integrated foreCast System[2], used for deriving forecasts beyond 6 hours, and the observation-based "nowcasting" technologies[3], used for short-term forecasts ranging from 0 to 6 hours. These technologies are integrated to derive irradiance forecasts. These irradiance forecasts are converted into expected electricity generation values, which are then provided to industry partners for real-time decision-making (Haupt *et al.*, 2018).

2 *The Dynamic Integrated foreCast System uses meteorological data (observations, numerical model output, statistical data, climate data, etc.) and produces tuned meteorological forecasts at user-defined forecast sites and lead times (NCAR Research Applications Laboratory, 2017).*

3 *Nowcasting combines the current state of the atmosphere with a short-term forecast of how the atmosphere will evolve over the next several hours (Mass, 2012).*

EWeLiNE, ORKA, ORKA2 and Gridcast projects improving VRE generation forecasts in Germany

Since 2012, the Deutscher Wetterdienst (German Meteorological Service) has been working on optimising its weather forecasts for renewable energy applications within the research projects EWeLiNE and ORKA, funded by the Federal Ministry for Economic Affairs and Energy. On the basis of the findings of the ORKA project in December 2015, this successful co-operation was continued in a new project, ORKA2, implemented in 2016, followed by a new project called Gridcast in 2017. In these projects, the German Meteorological Service and the Fraunhofer Institute for Wind Energy and Energy System Technology worked with the three German TSOs (Amprion GmbH, TenneT TSO GmbH and 50Hertz Transmission GmbH), one manufacturer of wind energy systems and two DSOs.

Their goal was to improve the weather and power forecasts for wind turbines and solar PV plants and to develop new forecast products focusing specifically on grid stability. These projects allowed them to use real-time data from solar panels and wind turbines around Germany and to feed those data into an algorithm that uses machine learning to calculate the renewable energy output. After testing, the researchers concluded that the newly developed forecast models have better forecast accuracy, with higher temporal and spatial resolution, than conventional models.

The new models also have better weather warnings, which are adapted to grid operation, especially when faced with extreme weather conditions, such as strong winds. Therefore, solar radiation data are calculated every 15 minutes, enabling the system operators to better estimate if they need additional resources to maintain grid stability. As a next step, the Gridcast project aims to integrate satellite images for solar forecasts in addition to the existing weather forecast data, thereby helping system operators better manage the system with high shares of VRE (IRENA, 2020).

Hybrid Renewable Energy Forecasting for advanced wind forecasting in China

The Hybrid Renewable Energy Forecasting (HyRef) project installed at a hybrid 670 MW solar and wind generation unit, created by IBM for the Chinese State Grid's Jibei Electricity Power Company Limited, is using advanced data analytics to improve the forecasting of wind power output. By using advanced tools for weather modelling, cloud-imaging technology and sky-facing cameras, paired with sensors on the wind turbine, HyRef can forecast the power output months ahead, but also up to 15 minutes before actual generation. As a consequence of using these technologies, wind curtailment has been reduced by 10%, which is the equivalent of supplying some additional 14 000 homes with electricity (Cochran *et al.*, 2013).

V. IMPLEMENTATION REQUIREMENTS: CHECKLIST

TECHNICAL REQUIREMENTS

Hardware:

- Smart meters to monitor real-time power production
- Weather sensors to continuously monitor changes in weather
- Wind turbine sensors to monitor the functioning of wind turbines
- Regional/national network of weather stations to continuously monitor weather patterns
- Sky imagers
- Satellite data

Software:

- Advanced weather forecasting tools based on a combination of input data (historical data, real-time data, etc.)
- Advanced power generation forecasting tools based on weather forecasting and power plant parameters (*e.g.* availability)
- Data analytics software (*i.e.* AI software, such as machine learning platforms)

Communication protocols:

- Common interoperable protocol co-ordination between VRE developers, asset owners, system operators (and consumers)

REGULATORY REQUIREMENTS

Retail market:

- Establish common open databases of weather data that can be accessed for free or at a small cost, which is necessary to bring down costs for smaller asset owners; these databases can have a large impact on the grid when aggregated
- Enable visibility of generation from distributed energy resources, like small-scale wind and solar PV generators (typically sub-megawatt)

Transmission and distribution system operators:

- Allow DSOs to monitor power generation data from distributed solar and small-scale wind projects
- Allow TSOs to integrate real-time VRE forecasts into the dispatch schedule
- Grid codes that cover data requirements for efficient VRE power generation forecasting

Wholesale market:

- Reward accuracy and penalise large deviations in scheduling and dispatch from market participants, where markets are in place

STAKEHOLDER ROLES AND RESPONSIBILITIES

Policy makers:

- Support the development of advanced forecasting tools for weather and VRE power generation
- Deploy mechanisms to record weather data at various locations to accurately forecast VRE power generation

System operators:

- Enable transmission and/or system operators to play the role of "data custodians"
- In liberalised markets, allow authorised third-party vendors to use data for developing new forecasting tools

VRE generators:

- Equip VRE plants with supervisory control and data acquisition systems, sensors and software for accurate power generation forecasts
- Make use of the most advanced weather forecasting technology for optimised VRE generation (to participate in markets or to inform system operators of the forecasted generation output)

Meteorological and research institutes:

- Collaborate with the renewable power industry, including system operators, to refine the weather forecasting tools to improve VRE integration into the power system

ABBREVIATIONS

AI artificial intelligence

ARENA Australian Renewable Energy Agency

CAISO California Independent System Operator

DSO distribution system operator

GW gigawatt

HyRef Hybrid Renewable Energy Forecasting

km² square kilometre

MW megawatt

NWP numerical weather prediction

PV photovoltaic

REMC Renewable Energy Management Centre

TSO transmission system operator

VRE variable renewable energy

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ADVANCED FORECASTING OF VARIABLE RENEWABLE POWER GENERATION
INNOVATION LANDSCAPE BRIEF

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