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Renewable energy power forecasting technology

National foreword

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TECHNICAL REPORT



Renewable energy power forecasting technology

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ELECTROTECHNICAL
COMMISSION

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INTERNATIONAL ELECTROTECHNICAL COMMISSION

RENEWABLE ENERGY POWER FORECASTING TECHNOLOGY

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The language used for the development of this Technical Report is English.

This document was drafted in accordance with ISO/IEC Directives, Part 2, and developed in accordance with ISO/IEC Directives, Part 1 and ISO/IEC Directives, IEC Supplement, available at www.iec.ch/members_experts/refdocs. The main document types developed by IEC are described in greater detail at www.iec.ch/standardsdev/publications.

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INTRODUCTION

The purpose of this IEC Technical Report (TR) is to describe common practices and the state of the art for renewable energy power forecasting, which includes general data requirements, methods for renewable energy power forecasting and forecast error evaluation.

Various stakeholders, including transmission system operators, transmission system owners, utilities, renewable energy generation plant developers, academic units, research institutions, certifying bodies and standardization groups, require a common understanding of renewable energy power forecasting methods, data and evaluation techniques so they can incorporate them in their operations.

Renewable energy power forecasting finds a broad application in many areas of electrical engineering related to design, analysis, market trading, and optimisation of the power system. Among others, forecasting could be as an input to the operation and management of the renewable energy generation plants and can improve the economic efficiency and reliability of the power system.

Renewable energy power forecasting is increasingly important in multi-stakeholder systems where renewable plant manufacturers, renewable energy generation plant developers and operators, as well as the power system operators, need to have a common understanding about the capabilities and methods associated with renewable energy power forecasting.

RENEWABLE ENERGY POWER FORECASTING TECHNOLOGY

1 Scope

This Technical Report, which is informative in its nature, describes common practices and state of the art for renewable energy power forecasting technology, including general data demands, renewable energy power forecasting methods and forecasting error evaluation. For the purposes of this document, renewable energy refers to variable renewable energy, which mainly comprises wind power and photovoltaic (PV) power – these are the focus of the document. Other variable renewable energies, like concentrating solar power, wave power and tidal power, etc., are not presented in this document, since their capacity is small, while hydro power forecasting is a significantly different field, and so not covered here.

The objects of renewable energy power forecasting can be wind turbines, or a wind farm, or a region with lots of wind farms (respectively PV systems, PV power stations and regions with high PV penetration). This document focuses on providing technical guidance concerning forecasting technologies of multiple spatial and temporal scales, probabilistic forecasting, and ramp event forecasting for wind power and PV power.

This document outlines the basic aspects of renewable energy power forecasting technology. This is the first IEC document related to renewable energy power forecasting. The contents of this document will find an application in the following potential areas:

- support the development and future research for renewable energy power forecasting technology, by showing current state of the art;
- evaluation of the forecasting performance during the design and operation of renewable energy power forecasting system;
- provide information for benchmarking renewable forecasting technologies, including methods used, data required and evaluation techniques.

2 Normative references

The following documents are referred to in the text in such a way that some or all of their content constitutes requirements of this document. For dated references, only the edition cited applies. For undated references, the latest edition of the referenced document (including any amendments) applies.

IEC 61400-12-2, *Wind turbines – Part 12-2: Power performance of electricity-producing wind turbines based on nacelle anemometry*

3 Terms, definitions and abbreviated terms

For the purposes of this document, the following terms and definitions apply.

ISO and IEC maintain terminological databases for use in standardization at the following addresses:

- IEC Electropedia: available at <http://www.electropedia.org/>
- ISO Online browsing platform: available at <http://www.iso.org/obp>

3.1 Terms and definitions

3.1.1

accumulation method

wind power forecasting method for wind farm clusters that directly accumulates the forecasting results of each wind farm output

3.1.2

combination approaches, pl.

approaches usually used to describe the forecasting models which combine physical approaches with statistical approaches

3.1.3

data assimilation

assimilation combining recent observation data with the background (prior) forecast in real time, to adjust forecast model trajectories and update the background field

Note 1 to entry: In numerical weather prediction (NWP), this helps the weather forecast become more accurate.

3.1.4

day ahead power forecasting

timescale used in forecasting, which is from the current time to the next 24 hours to 72 hours

3.1.5

days to week ahead power forecasting

timescale used in forecasting, which is from the day ahead to the week ahead

3.1.6

deterministic forecasting

kind of forecasting method that can output deterministic results

3.1.7

deterministic forecasting evaluation

evaluation of the specific forecasting value at a certain moment in the future

3.1.8

distributed PV power forecasting

a method to forecast the total power output of distributed PVs in a certain region

3.1.9

ensemble forecasting

NWP method which produces a set of forecasts instead of making a single forecast

Note 1 to entry: This set of forecasts aims to give an indication of the range of possible future states of the atmosphere.

3.1.10

event forecasting evaluation

evaluation of the forecasting results of specific events

Note 1 to entry: For example wind or solar ramp events.

3.1.11

horizon

length of the forecast look-ahead time

3.1.12

minutes and hours ahead power forecasting

type of forecasting which is in minute scale (up to 15 min) or ultra-short-term (15 min to 6 h or 8 h)

3.1.13

nonparametric modelling

distribution-free without any assumptions of the distribution type

Note 1 to entry: It directly calculates the quantile or distribution function of the unknown random variable by means of data analysis methods.

3.1.14

numerical weather prediction

NWP

method to predict weather which numerically solves the basic equations of atmospheric motion based on the most recent observations that best represent the current atmospheric conditions

3.1.15

parameterization schemes

methods to capture the quantitative physical characteristics of radiative, convective and diffusive processes in the atmosphere and at the interface between the atmosphere and the surface.

Note 1 to entry: These processes are often determined by relatively small spatial scales, and are used in NWP models.

3.1.16

parametric modelling

model to use a predetermined distribution type describing the probability density function (PDF) of the unknown random variable

3.1.17

persistence forecasting

a method to use the measured power value at the current moment as the forecasted power at the future time

3.1.18

physical approaches

mathematical and physical models which are used to describe the physical factors

3.1.19

power forecasting of renewable plant clusters

the forecasting of the overall output of wind or solar PV clusters

3.1.20

probabilistic forecasting

a kind of forecasting methods that focuses on the uncertainty of power output

Note 1 to entry: Including wind power probabilistic forecasting and PV power probabilistic forecasting. The forecasting results could be the PDF, cumulative distribution function (CDF) of the random variable of power or the prediction intervals at certain probability levels.

3.1.21

probabilistic forecasting evaluation

evaluation of the forecasting results of the uncertainty of power output

3.1.22**ramp events, pl.**

significant changes of power output in a short period

Note 1 to entry: These may refer specifically to those events not caused by the expected change due to the expected change in output of solar PV. Such events are prone to cause frequency fluctuation and power quality deterioration, potentially impacting the reliable operation of the power grid.

3.1.23**ramp magnitude**

variation of power output in the observation period

3.1.24**ramp rate**

variation rate of wind power in the observation period

3.1.25**resolution**

spatial or temporal scales at which forecasts are made, measured in kilometers (spatial) or minutes/hours

3.1.26**statistical approach**

mathematical model which is used to describe the relationship between historical NWP data, weather data and historical power output of a wind farm or a PV power station

3.1.27**statistical upscaling method**

establishment of an upscaling model with part of a set of points to estimate the total

Note 1 to entry: It is the total regional power output estimated from a subset of wind farms or PV stations.

3.1.28**stochastic process for forecast development**

stochastic process/model to incorporate random variation

Note 1 to entry: Usually based on fluctuations observed in historical data for a selected period using standard time-series techniques. The use of solely historical data is the main difference compared to probabilistic processes/models, which apply variations generated from some type of perturbation of the prediction process.

3.1.29**wake effect**

phenomenon of wind speed decreasing after wind turbines extract power from the wind

3.2 Abbreviated terms

AE	analog ensemble
ANN	artificial neural network
AR	autoregressive
ARMA	autoregressive moving average
BPNN	back propagation neural network
BS	Brier score
BSS	Brier skill score
CART	classification and regression tree
CDF	cumulative distribution function
CFD	computational fluid dynamics

CRPS	continuous rank probability score
CSI	critical success index
DC	direct current
EC	efficiency coefficient
ECM	ensemble composite models
ECMWF	European Centre for Medium-range Weather Forecasts
EMD	empirical mode decomposition
EPS	ensemble prediction system
ETS	equitable threat score
FAR	false alarm ratio
FBI	frequency bias index
FLA	fuzzy logic algorithm
GBM	gradient boosted machine
GEM	global environmental multiscale model
GFS	Global Forecasting System
GRAPES	global/regional assimilation and prediction system
GRNN	general regression neural network
GSM	global spectrum model
GSS	Gilbert skill score
HRRR	high resolution rapid refresh
HSS	Heidke skill score
IEA	international energy agency
ISSET	Institute of Solar Energy Technology
ISO	independent system operator
KDE	kernel density estimation
KNN	k-nearest neighbours
LS	logarithmic score
MA	moving average
MAE	mean absolute error
MAPE	mean absolute percentage error
MBE	mean bias error
MBPE	mean bias percentage error
MLP	multi-layer perceptron
MLR	multiple linear regression
MOS	model output statistics
MPE	maximum prediction error
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NWP	numerical weather prediction
PCA	principal component analysis
PDF	probability density function
POD	probability of detection
POE	probability of exceedance

PR	pass rate
PV	photovoltaic
PVPF	photovoltaic power forecasting
QDR	quantile deviation rate
QNDR	quantile negative deviation rate
QPDR	quantile positive deviation rate
QR	quantile regression
QS	quadratic score
RASS	radio acoustic sounding system
RBF	radial basis function
RBFNN	radial basis function neural network
ReIS	reliability score
RF	random forests
RMSE	root mean square error
RPF	renewable energy power forecasting
RPS	ranked probability score
RPSS	ranked probability skill score
RWP	radar wind profiler
SS	skill score
SVM	support vector machine
SVR	support vector regression
TDM	temporal distortion mix
TS	threat score
TSO	transmission system operator
TWRA	Tehachapi wind resource area
WPF	wind power forecasting
WPPT	wind power prediction tool
WRF	weather research and forecasting

4 General introduction to renewable energy power forecasting

4.1 History of RPF

4.1.1 General

Renewable energy has increased substantially in recent times, and is expected to continue to do so, due to a mix of policies encouraging uptake of renewables, cost reductions and societal preferences. Renewable energy includes wind, solar, tidal, geothermal, and biomass energy, but the development and utilization of renewable energy has mostly focused on wind and solar (particularly solar photovoltaic (PV)) energy in recent times. As the sources of wind and solar PV energy are both variable and uncertain, their output is also variable and uncertain. Large-scale integration to the grid has the potential to make it more difficult to balance power generation and consumption, which might significantly increase challenges related to power system operation. Uncertainty related to output can lead to increased operating reserve requirements, for example, or can result in curtailment of renewable output.

To help meet this challenge, many industry stakeholders have carried out research on wind and PV power forecasting technologies. Various advanced power forecasting systems have been developed to reduce the impact of uncertainty, improve ability of the system to consume renewable energy (by reducing curtailment) and ensure the efficient and reliable operation of the power system. Clause 4 introduces the development, usage and technologies used in renewable energy power forecasting.

4.1.2 Development of wind power forecasting

The development process of WPF can be divided into three stages. Before 1990 there was the initial stage; from 1990 to 2000 there was the stage of rapid development; and since 2000, various technologies have emerged rapidly, with a large number of commercial providers now offering their services in this area.

There are several historical overviews of state of the art wind and solar power forecasting technologies. The most extensive ones for wind power were by Giebel et al [1]¹ and Monteiro et al [2]. For solar power, Diagne et al [3], Inman et al [4] and the IEA [5] provided overviews, and Antonanzas et al [6] reviewed the subject and proposed common metrics. Kariniotakis' book [7] and a report by the Weather Intelligence for Renewable Energy COST Action [8] both offered an overview of wind and solar power together.

Brown, Katz and Murphy wrote the first paper to consider WPF in 1984 [9]. There, wind speeds were transformed to a Gaussian distribution, forecasted using an AR process, upscaled to hub height with a power law (whilst discussing the potential benefit of using a log law), and then the power was predicted using a measured power curve. Additionally, they discussed the removal of seasonal and diurnal swings in the AR components alongside forecasting intervals and probabilistic forecasts.

For pure time series models, in 1985 Bossanyi [10] used a Kalman filter with the last six values as input, obtaining a 10 % improvement in RMSE over persistence for one-minute averaged data, for forecasting the next time step. Many other authors reported the use of ANNs, FLA approaches, Box–Jenkins models and other AR efforts; a 10 % improvement in RMSE over persistence can be easily attained by a number of methods.

McCarthy [11] developed one of the earliest WPF models using offsite meteorological input for the Central California Wind Resource Area. It was operated in the summers of 1985–87 on an HP 41CX programmable calculator, using meteorological observations and local upper-air observations. The program was built around a climatological study of the site and had a forecasting horizon of 24 h. It forecasted daily average wind speeds with better skill than either persistence or climatology.

For any forecasting horizon beyond several hours, the use of NWP is necessary. In 1990, Landberg [12] and Troen [13] developed a short-term forecasting model, known as Prediktor, based on physical reasoning which is similar to the methodology developed for the European Wind Atlas [14]. The idea was to use NWP wind speed and direction, and adjust the winds according to the local characteristics, then apply a power curve, and finally modify it with the park efficiency. This model was first operationally used in a control room at Elkraft System, TSO for eastern Denmark in 1993. The Institute for Informatics and Mathematical Modelling of the Technical University of Denmark developed WPPT. WPPT has been running operationally in the western part of Denmark since 1994 and in the eastern part since 1999. The modelling system combines traditional linear models with conditional parametric models. For online applications, it is advantageous to allow the function estimates to be modified with available data. Furthermore, because the system may change slowly over time, observations should be down-weighted as they become older. The time adaptivity of the estimation is an important property because the total system consists of a wind farm or area and its surroundings, and the NWP model is subject to changes over time. This is caused by effects such as the aging of wind

¹ Numbers in square brackets refer to the Bibliography.

turbines, changes in the surrounding vegetation, and perhaps more significantly, upgrades in NWP models as well as changes in the population of wind turbines at a wind farm site or region.

In the late 1990s, the University of Oldenburg [15],[16], ARMINES [17], TrueWind [18] and ISET in Germany (now Fraunhofer IEE) also developed WPF systems. From the 2000s, many academic institutions started to develop WPF models, and companies were set up to commercialize these. Many global players are now jointly working together in the IEA Wind Task 36 on Forecasting [19].

4.1.3 Development of PV power forecasting

Compared with WPF, PV power forecasting started relatively late and the research methods and technical routes are also different due to the following aspects: (1) the solar movement law (which can precisely state the solar angle from astronomical principles) and atmospheric state fluctuation together lead to complex characteristics of irradiance fluctuation, and it is difficult to grasp the hourly variation in a day; (2) rapid and drastic changes of surface irradiance caused by the formation, dissipation, and motion of cloud clusters and variation in PV output may occur every minute in cloudy weather; this is difficult to capture in NWP models. In view of the above difficulties, scholars have carried out research on PV power forecasting using a variety of technical means and models and will continue to do so. Many of the same universities and companies which provide wind power forecasts also provide solar power forecasts.

Various institutes, including those in Europe, Asia and North America, have carried out research on solar PV forecasting since at least the early 2000s [20] to [22]. These can predict PV power output and perform resource assessment, as well as identify suitable locations for PV panels. Some are self-learning and self-calibrating systems based on physical models and advanced machine learning. These combine the historical data of output power, short-term NWP information, geographical information, calendar date and other factors, using an adaptive statistical model to predict the short-term output of a PV power generation system. Such systems have been providing power forecasting and optimization services for renewable power in Europe, North America, Australia, and other countries for more than 10 years.

4.2 Use of RPF

4.2.1 General

There are many studies on the benefits of using renewable energy power forecasting [23] to [25]. Different user groups may have different interests in electricity market and grid operation environments. For instance, system operators are interested in minimizing total system operational costs while maintaining a high level of reliability. In contrast, wind farm/PV plant operators are mainly interested in maximizing their income in the electricity market. The value of renewable energy power forecasting for TSOs and wind farms/PV plants is described separately below. It should be noted that there are now many forecasting companies (at least several dozen) across the world providing some or all of these services using a variety of combinations of the methods described later. All system operators that are integrating even relatively low shares of renewable resources have some type of forecasting system, typically procured from commercial providers though sometimes developed in-house. Such technologies are common and readily available, although, as discussed in Clause 10, there is a need to evaluate the forecasts provided by commercial providers.

4.2.2 RPF for system operations

For transmission system operators (TSOs) or independent system operators (ISOs), renewable energy power forecasting is one of the most cost effective measures for mitigating the results of variability and uncertainty. For TSOs/ISOs, renewable energy power forecasting systems are used for several purposes. For system operators, renewable energy power forecasting systems are used for two purposes that support their purpose of maintaining reliability. The first purpose is to facilitate the efficient scheduling of the system, which in market regions implies the buying (selling) of the amounts of renewable energy generation [26]. In many regions, such as Europe, this is primarily focused on the real-time market, which relies on renewable energy power forecasting updated every few minutes (though participants use the forecasts in day ahead also, TSOs tend to focus on real time operations). In the US ISOs, forecasts are also used in the day ahead processes, including day ahead markets and the day ahead reliability unit commitment. In the non-market regions day ahead (sometimes week ahead) and real time operations also require accurate forecasts.

The second purpose is to determine the amount of reserve capacity required to manage the uncertainty associated with renewables; in many regions this is set based on forecasted conditions, again at different look-ahead times from days ahead to real time. The assessment of the needs and participation in reserve markets are thus influenced by the forecast accuracy.

In recent years, many renewable power large-scale integration studies have been performed, with TSOs typically providing data backing these. A number of reports and facts from Denmark, the Netherlands, Greece, the United States, the United Kingdom, Spain, Ireland, etc., have shown that an accurate renewable energy power forecasting system plays a significant role in renewable energy integration. Therefore, sizeable efforts have been made to improve forecasting [27].

4.2.3 RPF for power trading

For wind farms/PV plants, renewable energy power forecasting is the basis for participating in the electricity market, where one exists. Short-term forecasting and ultra-short-term rolling forecasting comprise the most important information for generating schedules, bidding into the market, balancing any deviations the power plant is responsible for, and so on. For example, in Europe, the main functions are as follows: (1) In the day ahead markets, the wind farms/PV plants (often aggregated together as balancing responsible parties) participate in the market using day ahead forecasts [28]. Forecasts form the basis (together with any adjustments traders may want to make based on risk exposure) of the quantity of power that is traded in the day ahead market. If the shares of wind and solar are high, they may impact prices significantly, and can potentially result in negative prices, or prices closer to zero. If the forecast is poor, there may be a significant imbalance in the market that needs to be covered in real time. (2) In the intra-day market, the wind farms/PV plants adjust the hourly generation plan based on the rapidly updated ultra-short-term forecasting. Higher forecasting accuracy results in less balancing needed at the system level, and can result in reduced balancing payments and greater confidence in participation in the day ahead markets, where there is typically more liquidity. The narrower the gap between the generation plan and the real output is, the less TSO adjustment is required to regulate the market. As a result, the wind farm/PV plants' payments are reduced in some markets based on forecast error. In other regions, such costs are mostly socialized by the TSO.

In general, the accuracy and the application of the renewable energy power forecasting system helps inform the economic benefit of wind farms/PV plants. It is often the most important technical tool for the wind farms/PV plants to participate in the market profitably. Therefore, many professional trading teams include meteorologists, and buy their forecasts from several companies for security of supply, but also to improve the individual forecasts. Traders also use such forecasts to set their positions in the market, either with or without renewables in their portfolio.

In non-market regions, forecasts are used to determine fuel procurement, unit commitment and dispatch of conventional generation, and to set reserve requirements. They may also be used for trading with neighbouring regions.

4.2.4 RPF for operations and maintenance

Shorter horizons can also be considered for maintenance to ensure that crews can safely return from the offshore turbines in the evening. For example, in 2009 during a North Sea storm, a maintenance crew of the German offshore wind farm Alpha Ventus was trapped for 2 days due to the failure of early warning of weather prediction. The distribution system operator in German is integrating wind power forecasting into transformer maintenance routines to assess the line loading of rerouted electricity flows [29]. Additionally, even longer time scales would be interesting for the maintenance planning of large power plant components, wind turbines, or transmission lines. However, the accuracy of weather prediction decreases strongly 5 days to 7 days in advance.

4.3 Methods for forecasting renewable power

4.3.1 General

Wind power and PV power forecasting all need to consider the time scale of the forecasting plant, the spatial range, the type of input data and the forecasting model. Therefore, the division of WPF technology and PV power forecasting technology follows similar principles.

4.3.2 Classification of forecasting methods

Commonly used RPF technology classifications include those based on time scale, spatial range, modelling input data, forecasting model and forecasting form. The classification, characteristics, applicable scope, and typical methods of commonly used RPF techniques are summarized in Table 1.

Table 1 – Classification of RPF methods

Classification standard	Type	Characteristics and scope of application	Main model methods msed
Classification based on time scale	Minutes and hours ahead, intra-day (ultra-short-term)	Forecasts in this time scale predict the output in the next several minutes or hours. It can be used for commitment and dispatch, reserves optimization, situational awareness and trading.	Statistical extrapolation, assimilation methods (e.g. ensemble Kalman filter), and persistence method. For PV also use of sky-imagers.
	Day ahead (short-term)	Forecasts in this time scale can be used to make generation plans, optimize cold and hot standby, and rationally dispatch power grid resources, etc. For example, a method might predict the active power of the wind farm for three days with a time resolution of 15 min.	Physical method, dynamic statistics method.
	Days to week ahead (medium-term)	Forecasts in this time scale are mainly used to commit long start resources, schedule maintenance of power generation, transmission and distribution equipment, and schedule long duration storage resources.	Physical method based on NWP.

Classification standard	Type	Characteristics and scope of application	Main model methods used
Classification based on spatial range	Single turbine power forecasting	This method predicts the output power of a single wind turbine.	Physical method and statistical method.
	Single wind farm or PV plant power forecasting	This method forecasts the output power of a single wind farm or PV plant.	Physical method, time series method, and artificial intelligence method.
	Wind power cluster power forecasting	This method predicts the overall output of a cluster of power plants.	Accumulation, statistical method, and spatial resource matching method.
	Distributed PV power forecasting	This method predicts the overall output of distributed, often behind the meter, PV across a region.	Statistical, physical methods.
Classification based on modelling input data	Input data without NWP data	This method uses historical power data as the input to establish the forecasting model and deduce and the power forecasting results.	Statistical and machine learning methods.
	Input data using NWP data	With topographic and geomorphological information near the power plant as input, this method deduces physical information such as wind speed and direction or irradiation and temperatures through the micro-meteorological physical model, and it further obtains the forecasting power.	Physical method and artificial intelligence method.
Classification based on the forecasting model	Persistence method	Using the measured power value at the current moment as the predicted power at the future time, this method is simple and suitable for predicting short time scales.	Persistence method
	Physical method	Considering the physical information of the wind farm, this model uses NWP data instead of accumulating a large amount of historical data. It adopts the method based on wind speed, which is suitable for short-term RPF.	Physical method
	Statistical and learning methods	This method establishes the mapping relationship between NWP data and measured power, which is suitable for all horizons. This can use simple statistical methods or more advanced machine learning or other artificial intelligence methods	ARMA and Kalman filtering method, neural network method, SVM, deep learning, and gradient boosting method.
	Multivariate combination method	This is a kind of weighted average WPF method that combines the characteristics of the wind power data and meteorological data. It adopts the weighted average RPF method.	Forecasting based on time series method and neural network.
Classification based on forecasting form	Deterministic forecasting	This method provides the future point-by-point expected value of power. Its forecasting accuracy is typically high, but the forecasting cannot quantitatively reflect the uncertainty of wind power.	Physical method and statistical method.
	Probabilistic forecasting	The forecasting of prediction intervals or the density function of wind/solar power at a future time can be divided into the parameterized method, non-parameterized statistical methods and methods based on NWP ensemble forecasts.	Statistical methods such as QR, KDE, physical methods based on NWP ensemble.
	Event forecasting	The forecasting of the wind/solar power ramp event at a future time, focusing on the significant changes of power in a time period, which can be divided into the direct method and indirect method.	SVM, ASD and BPNN, NWP ensemble based forecasts, ensemble Kalman filter.

4.3.3 Classification based on time scale

The division of the forecasting horizon is affected by various factors such as forecasting feasibility, forecasting accuracy and usage demand. Although different countries and organizations do not have a unified standard for classifying the RPF horizon, research institutions and operators have divided RPF into ultra-short-term, short-term and medium-term. Forecasting of PV power at different spatial and temporal scales is shown in Figure 1. Introduced data for PV power forecasting at different spatial and temporal scales is shown in Figure 2. Similar methods can be used for wind power forecasting.

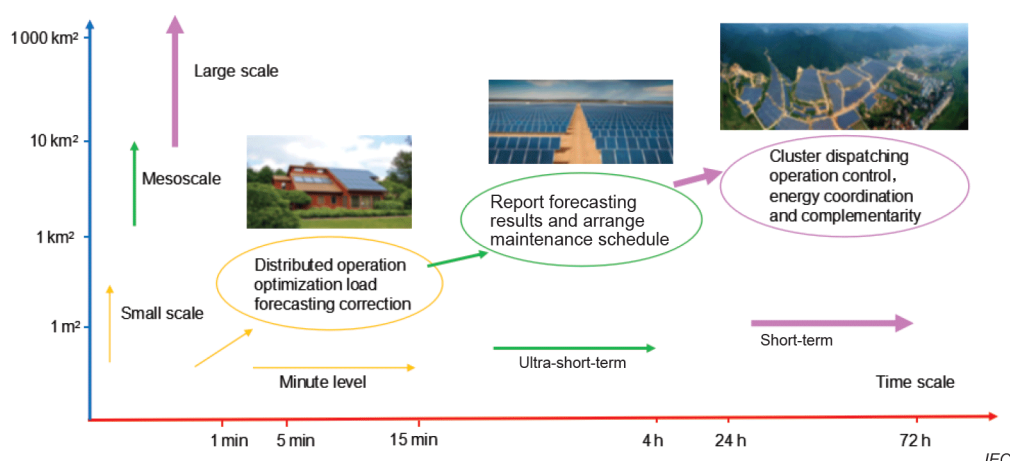


Figure 1 – Forecasting of PV power at different spatial and temporal scales

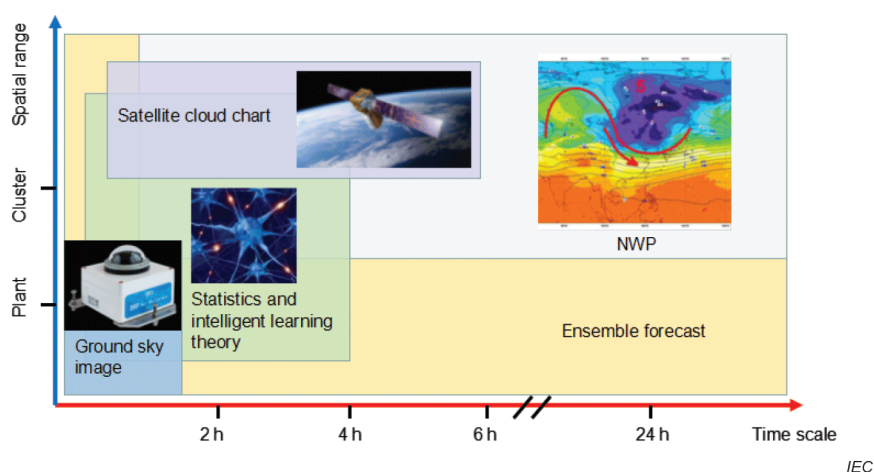


Figure 2 – Introduced data for PV power forecasting at different spatial and temporal scales

a) Minute and hours ahead

The forecast horizon of a few minutes to several hours (such as 4 h or 6 h) is sometimes called ultra-short-term forecasting, very-short-term or in more meteorological terms, nowcasting. Ultra-short-term forecasting is to predict wind/solar power 0 h to 8 h into the future. The use of forecasting in this time range is mainly for situational awareness, reserve procurement, short-term trading, balancing or economic dispatch, and commitment of quick start resources. Common methods for predicting renewable power in this time range are statistical extrapolation, two- and three-dimensional data assimilation methods (e.g. inverted ensemble Kalman filter [30]) and persistence methods using measurements of power output or meteorological measurements to assimilate or adopt long-term forecasts to the measurement state.

The time horizon of ultra-short-term power forecasting ranges from a few minutes to several hours, usually dependent on the validity of measurements to be used in the forecasting process.

For PV, surface irradiance is affected by the generation, dissipation, and motion of cloud clusters during cloudy weather, and its changes are variable, uncertain, rapid and severe, which seriously affects the accuracy of traditional forecasting algorithms. At the same time, a large number of field data shows that PV output fluctuates from 10 s to a minute scale in cloudy and fast-changing weather. Therefore, the predicted time resolution should correspond to the output fluctuation.

b) Day ahead

The time horizon of short-term renewable energy power forecasting ranges from the ultra-short-term limit up to 2 days or 3 days. In most European and many US markets, the main power trading is done before 12 noon for the coming day, i.e. based on forecasts 12 h to 36 h ahead. As an example, for State Grid Corporation of China, the requirement for short-term forecasting is to predict the wind power output of 72 h from 12 a.m. the next day with a time resolution of 15 min. China's short-term forecasting is mainly used to formulate a power generation plan. 48 h short-term forecasting in the United States is mainly used in the operation of the day ahead market (or unit commitment in the non-ISO regions), while 72 h short-term forecasting is mainly used to adjust the commitment of longer start resources, and to procure fuel and plan short-term maintenance. Similar time frames are used in Europe, Australia and elsewhere. Common methods for predicting short-term wind power are the continuous, physical, and dynamic statistics methods or physical power curve methods.

c) Week ahead and seasonal

Medium and long-term forecasting is generally used to predict the amount of electricity generated over seven days or even several weeks or months. Medium-term forecasting is mainly used to commit resources with long start-up, procure fuel, adjust maintenance schedules and adjust the operation of long duration energy storage. Week ahead and seasonal forecasting is mainly used to schedule maintenance in this time frame, and adjust very long duration storage (e.g. large hydro reservoirs).

4.3.4 Classification based on spatial range

This RPF method can be divided into single turbine or PV panel or roof installation power forecasting, single wind farm or PV power plant power forecasting and regional power forecasting according to the spatial scale of the research object. It should be noted that spatial scale and temporal scale are related – for example, second scale forecast for an entire wind farm is not going to give much realism, as the natural time scale of intra-wind farm smoothing is in the order of minutes.

Single turbine power forecasting refers to predicting the output power of a single wind turbine. The corresponding activity in the solar world is forecasting for a single PV panel or roof installation. Single wind farm power forecasting refers to predicting the output power of a single wind farm. At present, WPF research mostly focuses on single wind farms. Forecasting of an entire PV power plant is the equivalent.

Wind power cluster power forecasting refers to predicting the overall output of wind power clusters composed of multiple wind farms in a large space. Common wind power cluster power forecasting methods include the accumulation method, statistical upscaling method, and space resource matching method. For PV, similar methods are used for distributed PV forecasting, with a particular focus on those distributed PV regions where a large amount of the PV is behind the meter and therefore may not be directly observable to the system operator or those making forecasts. Spatial forecasts are described in more detail in the relevant wind and solar specific clauses later (Clause 8 and Clause 9).

4.3.5 Classification based on the forecasting model

According to different power forecasting models, RPF can be divided into persistence methods, physical methods, statistical learning methods, and multi-component combination methods. In addition, PV power forecasting has unique methods based on sky imagers and satellite cloud images.

a) Persistence method

The persistence method uses the measured power value at the current time as the predicted power at a future time. The model is simple, and its forecasting accuracy decreases rapidly as the forecasting time increases. It is usually applied to forecasting with shorter time scales. Smart persistence, which uses known information about the change in solar output based on the position of the sun, is often used for persistence PV forecasting.

b) Physical methods

The principle behind physical methods is to establish a fluid dynamics model that conforms to the meteorological characteristics of the wind farm based on the topographic and geomorphological information and physical information around it, and then use the model to predict wind speed and wind direction at the height of the wind turbine hub, leading to further predict the power of the wind farm. These methods have several important factors to consider. First, NWP data is needed to consider the physical information of the wind farm, rather than a large amount of historical data. Second, it does not correct for forecast deviations, for example in wind speed or irradiance. These make them more suitable for short-term RPF.

NWP-based power forecasting is currently the main method used in short-term forecasting with a time horizon of more than 4 h. NWP is a method for forecasting the atmospheric motion state and weather phenomena in a certain future time by numerically solving the fluid mechanics and thermodynamic equations that describe the weather evolution process. Due to the complexity of the evolution of weather conditions, it is generally necessary to rely on NWP to obtain meteorological data such as irradiance or wind speed to predict short-term and longer-term PV or wind power. The mapping relationship between predicted meteorological parameters and the output of renewable power plants can be constructed by physical or statistical methods to realize renewable energy power forecasting. NWP technology has been used in renewable energy power forecasting for many years and has performed well on the time scale of 6 h to one week.

c) Statistical methods

Statistical methods, used by themselves, do not consider the physical processes that impact wind and solar output. Based on an analysis of historical statistical and, if available, NWP data, they establish the mapping relationship between historical and/or NWP data and renewable output power. The methods directly use the historical and/or NWP data to predict the output power. They are applicable to ultra-short-term, short-term, medium-term, and long-term forecasting. Ultra-short-term RPF only requires historical data, while historical and NWP data is used together for short-term, medium-term and long-term forecasting. Compared with the physical method, the statistical method is simple and uses a single data source, but the processing ability of the mutation information is poor. Common statistical methods include ARMA, Kalman filtering and so on.

Traditional statistical methods have recently been enhanced by use of artificial intelligence methods, such as regression and machine learning; this has resulted in improvements in the subhourly time frame using just historical data, or multiple hour time scale using NWP data. These new methods use analytical equations to describe the relationship between input and output, while the former uses historical data, NWP data, or local time series extrapolated result data as input information to establish a nonlinear mapping relationship between output and multiple variables. Artificial intelligence methods require a large amount of historical observation data to build a model, but have the benefit of convenient modification and high precision. They are applicable to forecasting of all time scales. Ultra-short-term RPF only requires historical data, while historical and NWP data are used together for short-term, medium-term, and long-term forecasting. Commonly used artificial intelligence methods include various regression and machine learning methods, such as artificial neural networks, support vector machine (SVM), deep learning and gradient boosting methods.

d) Multi-component combination methods

Multi-combination methods combine the characteristics of renewable power data and meteorological data, i.e. the various methods above. They adopt the weighted average RPF method by applying different weights to different forecasting methods such as physical methods, statistical methods, and artificial intelligence methods to maximize the performance of each model and improve their forecasting accuracy. They include various machine learning and regression learning methods, and potentially other AI-based methods such as deep learning, etc. Most commercial forecasting systems use some form of combination approaches.

e) PV power forecasting method based on sky imagers and satellite cloud images

The main principle of this method, which is unique to solar, is to predict the distribution of future cloud clusters by tracking the cloud image in the sky image or satellite cloud image, then calculate the corresponding irradiance as well as solar power. The difference between the two kinds of images is mainly about the spatial resolution and update frequency of the images. Sky imagers are local and updated frequently, and as such mainly used for minute-level forecasting of a single solar power plant or local group of distributed PV, while satellite based forecasts cover a larger space, though are updated less frequently (minutes rather than seconds). They can thus be used to predict output from a few minutes to 6 h over a larger, but lower spatial resolution, area.

4.3.6 Classification based on the forecasting form

According to different forecasting forms, RPF can be divided into deterministic forecasting, probabilistic forecasting and event forecasting.

a) Deterministic forecasting

The forecasting content of deterministic forecasting is the expected value of renewable power in the future. The forecasting cannot quantitatively reflect the uncertainty of renewable power, which will lead to inevitable forecasting errors. Physical methods, statistical methods, artificial intelligence methods, and multivariate combination methods can all be applied to the deterministic forecasting of renewable power.

b) Probabilistic forecasting

Probabilistic forecasting uses NWP forecasting data as inputs to predict renewable power uncertainty information. It is an extension of single-point forecasting and can be used to assess the uncertainty of the power prediction for example for trading purposes, unit commitment, cut-off risks of wind farms, congestion or other operational risk factors in the power system. The forecasting content of probabilistic forecasting is the prediction interval or density function of power in the future, which can be divided into the statistical parameterized, non-parametric methods and NWP ensemble based methods. Typical non-parametric methods include quantile regression (QR) and kernel density estimation (KDE), while typical parameterized methods include vector autoregressive (AR) and generalized error distribution models. Typical NWP ensemble methods are the physical multi-model, multi-scheme methods or methods based on perturbation such as Monte Carlo, singular vector, breeding or ensemble Kalman filter methods (see also 5.5.2).

c) Event forecasting

Event forecasting is usually done in a statistical or a NWP ensemble based framework. The statistical methods use the random sequence of output power and the discrete renewable plant output power probability distribution to replace the power uncertainty and predict the output power probability distribution. These methods can describe the time correlation and spatial relevance of power in the future from historical data. Common scene generation methods include the Monte Carlo method, approximate Monte Carlo method, and optimal scene generation method.

The other methodology is based on NWP ensemble forecasts that generate a physical uncertainty of the current and future weather parameters of interest. The major difference is

this physical methodology is that it is capable of finding extremes in the forecasts, which are of special value when extremes did not happen before or have extreme long return periods and are not present in past historical training data.

4.4 Summary

Clause 4 introduced the historical development of wind and PV power forecasting technology across the world, and summarized the technical characteristics of the current common renewable energy power forecasting system. It also expounded on the role of power forecasting for different use cases, primarily system operations, power trading and plant operations and maintenance. And finally, it classified forecasts, based on time scale, spatial range, forecasting method and forecasting form. This helps identify how improvements and assessment of forecasting can be performed for different applications, based on the specific needs of the forecast user, for example for time horizon or spatial scale.

5 NWP technology

5.1 General

Renewable energy power forecasting, especially for the hours and day(s) ahead time horizon, requires the input of meteorological forecasting data, which is mainly fed from numerical weather prediction (NWP) model outputs. The predicted output power of wind farms and PV power plants is very sensitive to the accuracy of the NWP input data. NWP technology has several complicated processes that are introduced here. To improve forecasts, the factors that affect the prediction accuracy need to be analysed in detail, and targeted methods should be used to reduce the forecasting error.

5.2 Concept and characteristics of NWP

NWP numerically solves the basic equations of atmospheric motion given initial and boundary conditions and predicts the future state of the atmosphere from a best-known initial moment [31].

NWP is divided into two models based on spatial range: the global and regional models. The global model covers the entire world, and it solves synoptic-scale atmospheric conditions. There are currently fourteen National Meteorological Services in the world running global NWPs, including ECMWF's Integrated Forecasting System (IFS), the United States' Global Forecast System (GFS) of NOAA, UK Met Office's Unified Model (global configuration), the German Weather Service DWD's Icosahedral Nonhydrostatic (ICON) model, Canada's Global Environmental Multiscale Model (GEM), Meteo France's ARPEGE model, China's Global/Regional Assimilation and Prediction System (GRAPES), etc.

Global NWP models provide the necessary boundary conditions for regional NWP models. The horizontal spatial resolution of global models is generally on the order of tens of kilometers. Due to their lower resolution, global models struggle to reflect fine changes of the wind speed, clouds, and irradiance affected by local orography and sub-grid weather phenomena. Therefore, the NWP for RPF often requires a more refined regional model. The horizontal spatial resolution of regional models is generally several kilometers, which allows them to simulate the micro-terrain and micro-processes more accurately. In addition to higher horizontal resolution, regional models also benefit from more data assimilation cycles than global models, with new observation data being assimilated more frequently. This means regional model prediction results can be more accurate than those of global models. A few of the regional NWP models include the Weather Research and Forecasting (WRF), the UK Met Office's Euro4 and UKV models, DWD's COSMO-EU and COSMO-DE, Meteo France's AROME, and GRAPES-MESO model. The overall operational flow of a regional model is shown in Figure 3. Not all models will run exactly the same components, for example machine learning may not always be used in post processing.

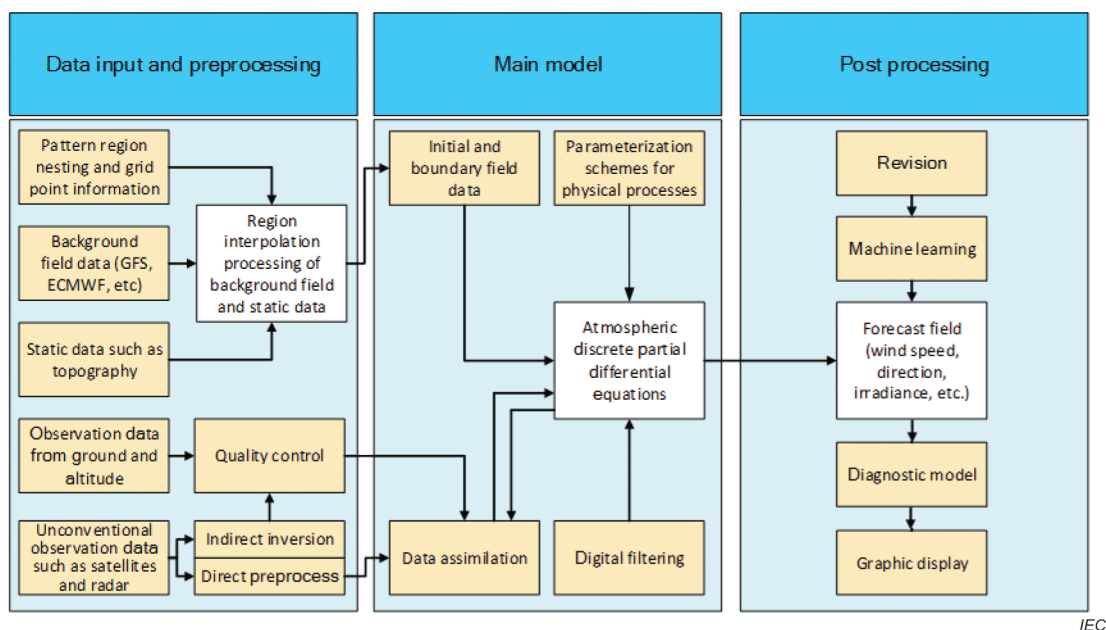


Figure 3 – Typical process for running a regional model

For RPF purposes, the most relevant meteorological fields are those closely related to renewable power generation (e.g. wind speed). Spatial and temporal resolutions are also important to help resolve small scale features. The paragraphs below highlight other specific requirements:

a) Focus on wind and solar

The magnitude of wind speed and solar irradiance directly determines the magnitude of wind power and PV output, so they are the most critical meteorological elements in power forecasting. However, to improve WPF accuracy, it is often necessary to introduce more weather fields, such as wind direction, temperature, pressure and humidity, etc. For PVPF, it is often necessary to introduce wind speed, wind direction and temperature, etc., in addition to solar irradiance.

b) Time resolution needs to be consistent with use case requirements

The purpose of RPF is to predict the output of wind and PV power to support the various use cases described in 4.2, including system operations, trading and operations and maintenance. For scheduling applications, wind and solar forecasts usually adopt a time resolution that is the same as the dispatch resolution of the system of interest, for example every 15 min in the hour ahead time frame, or hourly resolution in the day ahead time frame.

c) Quantitative forecasting

Deterministic NWP provides a single value weather forecast for a particular site and time. For example, at 10:30 on July 22, 2018, the wind speed of a certain point on a wind farm is 10,2 m/s, the wind direction is 93°, and so on. In addition, ensemble prediction systems (EPS) enable power quantitative probabilistic forecasting. This is given by a variety of probabilistic forecasting products, for example in the form of quantiles derived from the ensemble PDF, or individual outcomes from each ensemble member.

d) Forecasting look-ahead is consistent with needs of the use case

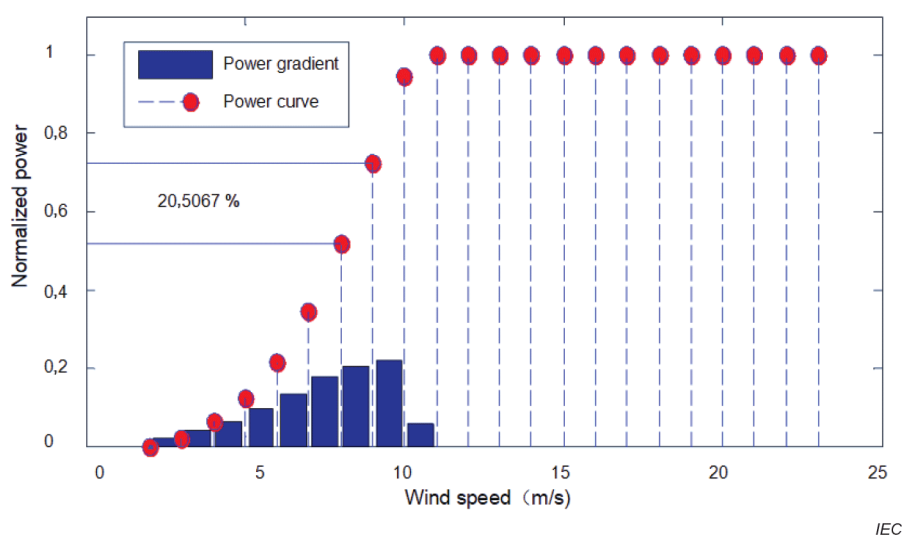
The look-ahead should be as long as that used for the processes in which they are integrated. For example, for unit commitment models used in power system operations, the look-ahead might need to be at least 72 h, and as much as a week ahead. This varies depending on the system of interest and should be based on characteristics of the power system.

5.3 Influence on RPF accuracy

5.3.1 Sensitivity analysis

NWPs of wind speed and solar irradiance are the most critical inputs for the RPF model, and the key factors affecting power forecast error. Taking WPF as an example, at the steep part of the power curve, the wind power is proportional to the cubic of the wind speed, meaning the power is very sensitive to any variations in wind speed. The power curve of typical wind turbines is shown in Figure 4. As illustrated in the power curve shown in Figure 4, when the wind speed is 8 m/s, if the predicted wind speed deviates by only 1 m/s, the predicted power error will reach 20,5 %. Therefore, power forecasting is very sensitive to the NWP error. Much of the time, wind turbines operate in the steep part of the power curve, which leads to NWP bias being the main source of wind power prediction error.

NWP skill, namely that for wind speed and irradiance, varies across different regions, phenomenal scales and historical distribution of weather events. Generally speaking, the forecasting error of complex terrain and land cover is larger than that of flat terrain and single land cover. Compared to large-scale weather phenomena (e.g. frontal winds), the forecasting error of a convective-scale process (e.g. turbulence) can be larger. For example, in China, the forecasting error in the northwest region is generally higher than that in the eastern coastal areas, mainly due to the complex terrain in the northwest, changeable dominant weather system, and scarcity of observation data. The limitation of historical data available may also compromise the analysis of extreme weather events, leading to biased results [32]. The use of extreme-value theory may hence be applied to avoid a biased statistical analysis of severe and rare weather events.



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Figure 4 – Power curve of typical wind turbines

Figure 5 shows an example of time series of predicted (blue) wind speed and solar irradiance compared to what was observed (red) at a specific location, highlighting three types of deviations. The first is amplitude deviation—that is, where the trend is accurately predicted, but the maximum and minimum values of the fluctuation appear to differ significantly. The second is phase deviation—that is, where the amplitude of fluctuation is accurate, but the time of the fluctuation deviates from the actual. The third is other deviations—that is, where the deviation characteristics cannot be attributed to the first two, for example, a missing forecast or complete anti-phase of a fluctuation process often occurs when the simulation process has a large error. Wind power ramp events may be caused by sudden and/or large variations of the wind, and changes in cloud cover may lead to PV power fluctuations. Variations in wind and solar resources, leading to fluctuations in power forecast and an increase in the prediction error, can be revealed by the above three kinds of errors.

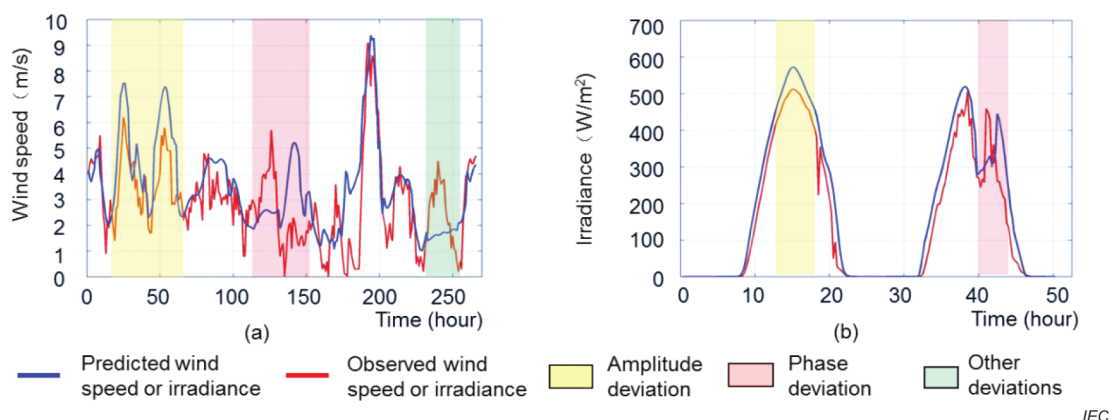


Figure 5 – Characteristics of three kinds of forecasting errors

5.3.2 Error source analysis

There are no perfect models; by definition, they are incomplete representations of the systems they aim to simulate. Given the complex physical phenomena and dependencies being represented in NWP models, the sources of error and uncertainty are manifold. First, the NWP model is a discrete computing system of continuous time and space, which inevitably leads to incomplete representations of the orography and meteorological fields. The computing machines used to perform those calculations are also limited by the number of significant digits they are able to compute. Second, the observation data is limited, and the instruments taking measurements also have limited sensitivity. These contribute to errors in the NWP background field, as the observed data is assimilated into the model at that stage. In addition, parameterization schemes describing the sub-grid and micro-scale phenomena, such as turbulence, radiation, clouds and aerosols are not perfect, because their internal mechanisms and interaction with other atmospheric components are complex, not yet fully understood and formulated. Finally, the atmosphere is an extremely chaotic and nonlinear system. As an initial value problem model, this means that the equations describing the dynamics of the atmosphere and its thermal processes are highly sensitive to the initial conditions of the NWP. Therefore, the uncertainty in NWP increases with the forecast lead time.

There are different ways to account for and reduce NWP errors, many of which are undergone as an integral part of a model suite, in various post-processing stages, for example, by using in-situ observations to reduce systematic biases. In addition, uncertainty in the weather forecast is addressed by running ensemble prediction systems. Ensembles are generated by making controlled changes to the initial conditions, in order to emulate the chaotic behaviour of the atmosphere. The different output scenarios are then analysed to quantify the uncertainty in the forecast. Thus, a combination of methods is required to reduce NWP errors. The paragraphs below address the three types of NWP error described in 5.3.1.

a) Amplitude deviation

Despite the increase in horizontal spatial resolution of mesoscale regional models, the acceleration or attenuation of wind speed caused by sub-grid orography cannot be accurately described. Where physical corrections accounting for orographic and height adjustments, or other statistical corrections, have not been applied on a post-processing stage, this may result in a systematic amplitude deviation.

Sub-grid processes leading to cloud formation and movement, aerosol and dust dispersion, among others, affect the amount of solar irradiance that reaches the ground or plane of array. These are parameterised in the NWP model, which may contribute to a systematic amplitude deviation.

b) Phase deviation

Phase deviation means that, although the corresponding value has been correctly predicted, it has been so at the wrong time.

For irradiance, the main contributor to spatial deviation is the deviation of the predicted positions of cloud clusters [33], [34]. Due to the error of the relevant parameterization scheme and the low resolution of the model itself, it is difficult to accurately simulate the location of cloud clusters.

c) Other deviation

NWP sometimes does not predict the actual fluctuation process or predict complete anti-phase of the fluctuation, indicating that there is a large forecasting error which may be due to background field, parameterization scheme, micro-topography, observation data, or calculation accuracy, etc. It may also be caused by the sensitivity of initial errors of the NWP model in the forecasted region and period.

5.4 Technology progress for improving NWP

5.4.1 General

NWP global configurations provide boundary data to drive nested higher resolution regional models. Subclauses 5.4.2 and 5.4.3 describe the main characteristics of global and regional models.

5.4.2 Global model

Global models are complex, with details for the entire world. In addition to the atmospheric motion calculation contained in the regional model described next, the global model also contains calculation of the motion of the ocean, ice layer, etc. The major weather centres' computing ability keeps growing, but the complexity of the global models is also limited by the delivery times of the assimilated data and the necessary output, for example, if an operational global model runs 4 times a day, then the cycle of data intake, assimilation, model run and output preparation shall reliably be over within 6 h, which limits the resolution and amount of ensemble members a weather centre can deliver. There are currently a dozen national meteorological departments in the world that are able to produce and operate global models, with a smaller number of private companies also running these. Two relevant examples include:

- The European Centre for Medium-Range Weather Forecasts (ECMWF) is an independent intergovernmental organization supported by 34 states. As a research institute and an operational service, it invests in scientific and technical research to improve global NWP, through international collaboration. Figure 6 shows ECMWF's forecast skill for the 3-, 5-, 7-, and 10-day forecasts, over the Northern and Southern hemispheres. The skill over the forecast range has improved by about one day per decade, for the past 40 years. This means that the 7-day ahead forecast today is about as skilful as the 5-day ahead forecast was back in the 1990s. The convergence of the Northern Hemisphere and Southern Hemisphere curves is a result of developments in the satellite data assimilation scheme, whereby 3-D Var was upgraded to 4-D Var.
- The National Centers for Environmental Prediction, which is part of the United States National Oceanic and Atmospheric Administration, runs the Global Forecast System (GFS). The GFS background field is widely used in the world.

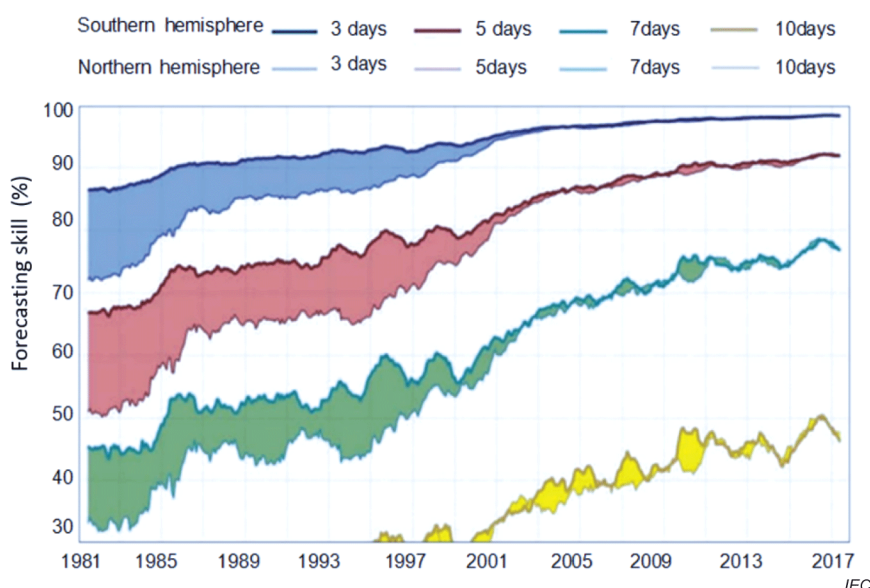


Figure 6 – Evolution of ECMWF's forecasting skills for the 500 hPa potential height [35], [54]

The growth of computing power available for meteorological research and forecasting has allowed for a continuous increase in global NWP model resolutions. Table 2 shows the main forecasting features of global NWP models around the world. The highest horizontal resolution reaches $0,1^\circ \times 0,1^\circ$. However, refinement creates a problem where increased data take longer to download and calculate. Therefore, many organizations today provide background field data of $0,5^\circ \times 0,5^\circ$ or even $1^\circ \times 1^\circ$ resolution.

The resolution of the global model is likely to continue to become more refined in the future. The coupling effect among the atmosphere, land, and ocean will also be improved. The data assimilation method tends to use the hybrid assimilation of four-dimensional variation, Kalman filtering, and ensemble methods, etc., to absorb more sophisticated observational data. These actions will improve the forecasting quality of wind speed, ground irradiance, clouds and vapour, etc., and are described as areas of future research in the conclusions clause (Clause 10).

Table 2 – Features of global NWP models

Model	Producer	Horizontal resolution	Vertical layers No.	Time resolution	Forecasting length	Space discretization
GFS	America NCEP	$0,25^\circ \times 0,25^\circ$	64	1 h	16 days	Quadrilateral grids
FV3	America NCEP	$0,125^\circ \times 0,125^\circ$	64	1 h	16 days	Hexagonal grids
ECMWF	Europe ECMWF	$0,1^\circ \times 0,1^\circ$	137	1 h	10 days	Spectrum
GEM	Canada CMC	$0,14^\circ \times 0,14^\circ$	84	3 h	10 days	Quadrilateral grids
GRAPES	China CMA	$0,15^\circ \times 0,15^\circ$	90	3 h	10 days	Quadrilateral grids
GSM	Japan JMA	$0,25^\circ \times 0,25^\circ$	100	3 h	11 days	Spectrum
UM-Global	UK Met Office	$0,1^\circ \times 0,1^\circ$	70	1 h	6 days	Quadrilateral grids
ICON	Germany DWD	$0,125^\circ \times 0,125^\circ$	90	1 h	7 days	Icosahedral grids

Model	Producer	Horizontal resolution	Vertical layers No.	Time resolution	Forecasting length	Space discretization
ARPEGE	Météo France	0,1°× 0,1° for Europe, 0,5°× 0,5° for other regions	105	3 h	5 days	Stretching Spectrum
NAVGEN	America FNMOG/NRL	0,28°× 0,28°	50	3 h	7,5 days	Spectrum
GDAPS	Republic of Korea KMA	0,1°× 0,1°	70	1 h	12 days	Quadrilateral grids
ACCESS-G	Australia BoM	0,25°× 0,25°	70	1 h	10 days	Quadrilateral grids
NCUM	India NCMRWF	0,125°× 0,125°	90	1 h	10 days	Quadrilateral grids
BESM	Brazil CPTEC/INPE	0,1°× 0,1°	64	1 h	10 days	Quadrilateral grids

5.4.3 Regional model

A regional model benefits from higher resolutions, enabling more accurate microphysical and convection-permitting schemes, more detailed surface orography modelling, etc. Regional models are more widely used in power forecasting than global models. They are driven by the coarse resolution data from global models, and generally have a resolution from 1 km to 10 km. A large number of regional observation data can be absorbed into regional models by using many assimilation methods. Several relevant examples include:

- The WRF model developed by NCAR is the most widely used regional model. After more than 20 years of development, WRF has many numerical methods and physical process parameterization schemes with multiple grid nesting capabilities. WRF also has many data assimilation interfaces, for example WRF-DA, GSI, DART, etc. As for irradiance prediction, NCAR developed the WRF-Solar model based on WRF and improved the physical parameterization scheme of aerosol, cloud microphysics, and radiation interaction, which can assimilate satellite and other irradiance data.
- The regional model UKV of the Met Office operates in a fine grids resolution up to a 1,5 km inner domain and a 4 km outer domain; its initialisation of the atmosphere is by 4D-VAR data assimilation with hourly cycling.
- The DWD COSMO-DE regional model in operation has a 2,2 km grids resolution and a 3 h cycling, and encompasses many local details of the landscape and related flow phenomena that are not contained in DWD global model ICON.
- The regional model of Météo France in operation is AROME-HD, it has a 1,5 km resolution and 6 h cycling.
- The regional model of the China Meteorology Administration in operation is GRAPES-MESO. It has a resolution of 3 km × 3 km, and has a 3 h cycling.

The above list is non-exhaustive and intended to illustrate different models, which are under constant development and improvement. Subclause 5.5 introduces key technologies to improve the prediction accuracy of the regional model—especially for wind speed and solar irradiance.

5.5 Key techniques for improving the forecast accuracy of regional models

5.5.1 Improve the accuracy of the initial conditions

Operating the regional model requires initial and boundary conditions. For short-term forecasting, the initial conditions are more important than the boundary conditions (for long-term climate prediction, the boundary conditions are more important than the initial conditions), and largely determine the accuracy of the short-term forecast. The improvement of the accuracy of the initial conditions is mainly reflected in the following aspects:

a) Meteorological satellites and radar observation data assimilation

Data assimilation makes the best use of observations data and background forecasts to adjust the initial field and move it closer to reality. Often, large-scale PV and wind power plants are installed in remote and sparsely populated areas. However, meteorological observation stations in these areas are often relatively sparse, and there is not enough observation data for assimilation. Meteorological satellites and radars may have a wide range of observations in potential sites for deploying wind and/or solar farms. This contributes to improving the accuracy of wind and solar forecasts [36], [37]. Currently, most satellite and radar assimilation methods are based on the variational method. The assimilation provides the benefits of initial field improvement, especially for surface water vapour, aerosol, dust, clouds, and irradiance.

b) Wind and PV power plants observational data assimilation

Wind and PV power plants generally have station observation devices. The standard observations of wind farms include the wind speed and wind direction at 10 m, 30 m, 50 m, 70 m, and at hub height. The standard observations of PV power plants include the global horizontal irradiance, direct normal irradiance, diffuse irradiance, air temperature, air pressure, relative humidity, total cloud cover, etc. Introducing local observations may help improve the accuracy of the forecast. If only the observation data of a single station is assimilated in the model, the assimilation can only work in the first few hours of the forecast, because the correction of the initial field by a single observation point will disappear with the movement of the atmosphere. But if the observation data of a cluster of plants is used, the assimilation effect will be prolonged.

There are also some challenges when aiming to incorporate these observations into assimilation: observation quality control is necessary according to existing standards, for example WMO's standards, the observation instruments need to be calibrated regularly, the observation data shall be sent on time for data assimilation, etc. These local wind/solar farm observations can also be used in the post-processing stages to reduce forecasting errors.

For the situation where there is no observational data of wind farms and PV power plants, as much data as possible from adjacent observation sites should be collected.

c) Rapid update cycle for regional models

In the regional model running process, if the initial field is from the global background field, this is called a cold start. If the initial field is from the last forecasting result, this is called a warm start. The cold start has no cloud and water vapour information at the beginning; cloud and water vapour are gradually generated by the parameterization scheme. The warm start may retain the cloud and vapour information, but after several warm start forecasting, the forecast field may deviate greatly from the real. To rationally reduce cold start times and increase warm start times may bring benefits: computing time can be reduced as the cold start times are reduced, and the accuracy of the meteorology field can be promoted by this combination of cold start and warm start. This process is also called rapid update cycle (RUC). With the aim of not deviating from the big background field, RUC is in favour of assimilating satellite and radar data more frequently.

5.5.2 Ensemble prediction systems

5.5.2.1 General

The ensemble forecasting method has become a widely used approach to deal with the initial error sensitivity of NWP [38] and general uncertainty of the weather forecast from the deterministic models [39]. An ensemble forecasting sketch is shown in Figure 7.

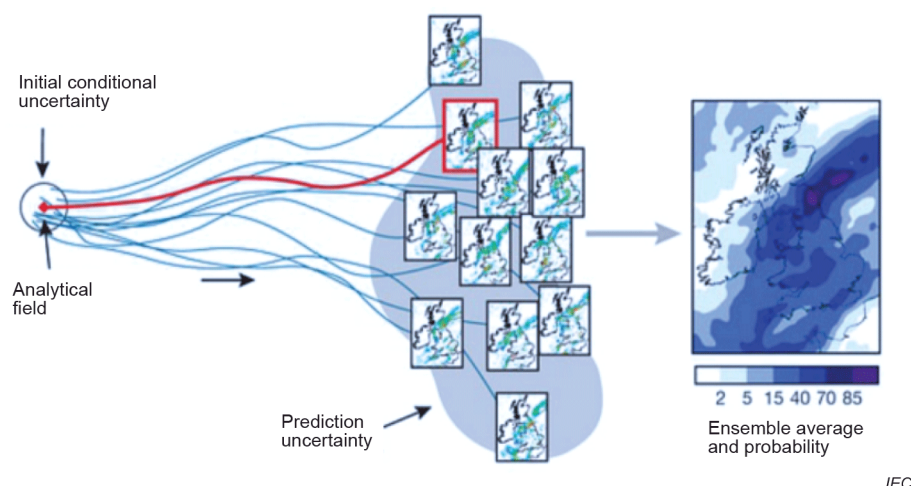


Figure 7 – Ensemble forecasting sketch [54]

Ensemble forecasting started in the 1990s (see e.g. [39] to [46]) as a means to provide information on risk management to society, where the first operational ensembles forecasting system was started in 1993.

Cheung's review of ensemble forecasting techniques (2001) [47] provides a comprehensive summary of the available methodologies and developments since the 1990s. The most important aspect to understand regarding ensemble forecasting is that an ensemble consists of a collection of forecasts that together estimate the inherent uncertainties in a numerical forecast. A properly designed ensemble should be a finite approximation of the probability density function of the atmospheric state in phase space. In other words, each ensemble member should ideally be an equally probable state of the real atmosphere.

The method of producing perturbations depends on the particular system under consideration and its associated spatial scale. The simplest way is to add random noise to the original analysis (termed as Monte Carlo forecast [48], see 5.5.2.2), but this is not an optimal method because the error characteristics in an analysis are often organised or correlated in some way. The ensemble approach requires the distribution of perturbations to be close to that of the initial state errors. This distribution in general is unknown and explains why the perturbation methodology is central to any discussion on ensemble forecasting [49].

Here the focus is on the aspects concerning the power industry and the challenges of applying various techniques for operational forecasting of wind and solar power at system operator level, at utility scale and for balance responsible parties. A more detailed description of the methodologies can be found in [47].

5.5.2.2 Monte Carlo approach

The principle of Monte Carlo forecasts is to produce random samples of an expected outcome, build a probability density function (PDF) and analyse the statistical behaviour of the outcome. Harrison [48] described the overall intention of Monte Carlo simulation as simulations that use random sampling and statistical modelling to estimate mathematical functions and mimic the operations of complex systems.

Monte Carlo simulations have a long history in statistics and any type of description of uncertainty. In the context of weather forecasting, they have also been the forerunner of today's ensemble forecasting systems. The difficulty of the approach comes with the size of the sample. Zhang and Pu [49] estimate that for a common real-model with 107 degrees of freedom, a 107×107 dimension calculation for estimating the PDF will be involved. This deficiency of the Monte Carlo simulations meant that since the early 1990s, other methodologies have been developed and brought into operation.

5.5.2.3 Initial conditions perturbation approach

The ensemble approach with the next longest history of operational use is those approaches where the initial conditions are perturbed. A large number of ensemble prediction systems exist today (see e.g. the TIGGE project [50]). The most common methods are:

- Breeding vector method

This method is based on the argument that fast-growing perturbations develop naturally in a data assimilation cycle and will continue to grow as short- and medium-range forecast errors.

- Singular sector method

In the singular vector (SV) based method, the directions of the fastest perturbation growth are identified (see e.g. [51], [42]). Singular vectors maximize growth over a finite time interval and are consequently expected to dominate forecast errors at the end of that interval and possibly beyond. Instead of using a selective sampling procedure, initial conditions may be assimilated with randomly perturbed observations [52], using different model versions in a number of independent data assimilation cycles. This Monte Carlo like procedure is referred to here as the perturbed observation (PO) approach [53].

One of the main characteristics of these approaches is that they work with so-called target times or areas. This means that the uncertainty generated by the perturbations is only valid at that target time or area. This is worth noting, because for most applications in the power industry, especially wind energy and PV forecasting, there exists a discrepancy between such meteorological lead times of these ensemble techniques and the requirements of uncertainty in the power industry. While meteorologists focus on specific times such as 24 h ahead or 72 h ahead, the power industry has a need to know the uncertainty in a continuum, i.e. in every time step of the forecast.

The major calibration methods to circumvent such issues will be given in 5.5.2.5.

5.5.2.4 Physical approaches

The only ensemble techniques that have inherent physical computations of uncertainty in every hour of the forecast lead time are the multi-model technique and the multi-scheme technique, which will be described briefly hereafter. A more detailed description of these methods and examples can be found in [47].

a) The multi-model approach

The multi-model approach uses the output of many different deterministic forecast models to create an ensemble. The drawback of this approach is that a multi-model ensemble is likely to be rather under-dispersive, because deterministic models usually suppress extremes and thereby generate too little spread. There are other disadvantages with the multi-model approach such as the difficulty to maintain many different NWP models or even collect output data from many different NWP models. However, the most critical issue with multi-model ensembles in operation is certainly the fact that deterministic models are tuned to provide best average forecasts, which often means that extremes are suppressed and therefore missed. Without extremes, the forecast spread however will not resemble a realistic uncertainty and the probability density function will be skewed. To overcome such skewness, post-processing methodologies are necessary.

b) The multi-scheme approach

The multi-scheme approach was developed due to the needs for limited areas and short-range probabilistic weather prediction, driven by studies for flooding risks [55].

The predictability horizon for precipitation as well as for other surface or near-surface variables such as wind, radiation temperature, is shorter than for more conservative parameters like mean sea level pressure, geopotential height or even upper level temperature. It is well known that those processes that cannot be explicitly resolved in the numerical models have to be approximated through different parameterization schemes. And it is exactly these schemes that are major sources of model error [54].

The success in the form of ensemble spread, correctness and consistency of the probability distribution of the multi-scheme ensemble members is however closely dependent on the choice of processes that are computed differently within the numerical prediction model. If the chosen processes that have varied formulations are not directly connected to the variables that are under focus, the spread and hence uncertainty estimate and the skill of the ensemble to predict the uncertainty of specific variables lose their value [47].

For the application in the power industry, this also means that a multi-scheme approach needs to be designed or calibrated to the target variables in order to generate the desired uncertainty of the variables responsible for the wind and/or solar generation. Here, the fast meteorological processes of (1) dynamical advection, (2) vertical mixing and (3) condensation are most relevant for the simulation of fronts and the friction between the atmosphere and the earth's surface relevant for wind and solar forecasting.

The multi-scheme approach has been demonstrated for other surface or near-surface variables to be the only approach that combines the advantages of the physical uncertainty computation with a reasonable computational effort. This is so, because the kernel of the NWP model is the same for all ensemble members. Specific physical and dynamical processes are then computed with different, but physically equivalent approaches [56] to [58]. Meng and Zhang [58] found in their experiments of a severe storm that a combination of different parameterisation schemes has the potential to provide better background error covariance estimation and smaller ensemble bias.

c) Ensemble Kalman filter approach

The ensemble Kalman filter (EnKF) method was first described by Evensen in 1994 and later by Houtekamer and Mitchell in 1998 [59] to [61]. EnKF became feasible in the context of operational atmospheric data assimilation around 2005. EnKF has its base in the computation of the background error covariance. The difficulty in the approach lies in that the true state of the atmosphere is unknown. This makes the estimation of the background error covariance difficult and expensive [49].

An example of an EnKF ensemble is the EnKF EPS at the Meteorological Service of Canada that has been used operationally since 2005 as a medium-range ensemble prediction system (EPS) and since 2007 as a short-range EPS, [61] to [63].

In the Canadian EnKF algorithm, a strategy currently with four sub-ensembles [60], [64] is used to preserve a representative ensemble. Consequently, in the absence of any differences between the model and the atmosphere or between the true and assumed observation-error statistics, the EnKF should maintain ensemble statistics that are representative of the actual error in the ensemble mean. It is thus possible to predict the analysis quality from the ensemble statistics for a hypothetical environment without model error. The negative impact of the different sources of model error on forecast quality can subsequently be quantified from the increase in ensemble spread as these components are added to the EnKF environment [63].

5.5.2.5 Ensemble calibration methodologies

It is only recently that the energy meteorology research community has developed ensemble calibration methodologies for the output from ensemble prediction systems using stochastic perturbation methods such as singular vectors or breeding [41], [42]. The issue with these approaches is that they are designed for specific lead times, which are usually greater than 48 h. It means that the spread between the ensemble members is too small in the beginning of the forecast and often too large at the end of the forecast. In the scientific community, these problems are referred to as under-dispersiveness and over-dispersiveness, respectively. The first shows so-called u-shaped histograms, while the latter shows bell-shaped histograms when the spread is evaluated objectively [65], [66].

To get around this issue, calibration methods have been developed, such as ensemble model output statistics (EMOS) methodologies [65], [66] and derivatives thereof, such as:

- BIAS corrections on each ensemble member
- bivariate EMOS [67]
- variance deficit calibration [68]
- ensemble kernel dressing [68]
- Bayesian model averaging [69]
- bivariate ensemble copula coupling [70]
- analogue ensemble calibration [71]

Univariate or bivariate Bayesian model averaging techniques are theoretically also useful, but their high computational costs and similar performance compared to EMOS approaches mean that they are not considered for practical applications at present [72].

5.5.2.6 Importance of the correct choice of ensemble forecasts

It is well-known among meteorologists that forecast errors in real-world applications arise not only because of initial errors, but also because of the use of imperfect models. Representing forecast uncertainty related to the use of imperfect models is thought to be of an even greater challenge than simulating initial-value-related errors [54]. The deficiencies and benefits of the various approaches are hence an imperative aspect to consider when choosing probabilistic forecasts for real-world applications such as wind power or solar power forecasting. In fact, the success and the value of using probabilistic forecasts is dependent on the correct choice of methodology and requirements to fulfil a specific task [47].

Because of the inherent risk in forming an ensemble with a number of deterministic models, the spread that determines the model error may not be consistent and rather small, because deterministic models often tend to suppress extremes, which are required to form a realistic description of model errors in the atmosphere.

Using an EPS formed with stochastic perturbations, a multi-scheme approach or EnKF for wind power or solar power predictions is therefore fundamentally different from using one consisting of a few deterministic weather prediction models, because severe weather and critical wind power events are different. The severity level increases with the wind speed in a weather context, while wind power has two different ranges of winds that cause strong ramping, one in the middle range and a narrow one just around the storm level (the cutoff level). Wind power forecasting models therefore have to be adapted to the use of the ensemble data.

In general, a wind power prediction model or module that is directly implemented into an EPS is different from traditional power prediction tools, because the ensemble approach is designed to provide an objective uncertainty of the power forecasts due to the weather uncertainty and requires adaptation to make use of the additional information provided by an ensemble [47].

Table 3 provides an overview and comparison of different ensemble forecasting technologies and their applicability in the power industry as aid in understanding and choosing the correct method for the application at hand.

Table 3 – Comparison of different ensemble prediction methodologies and their attributes [46], [73]

Approach	Monte Carlo simulations	Ensemble Kalman filter	Initial condition perturbation	Multi-model	Multi-scheme
Method	statistical	statistical	statistical	physical	physical
Member differences	random statistical perturbations of the initial conditions ("analysis")	statistical perturbations from linearised equations – forecast error covariance	non-linearised lyapunov (bred) vectors or singular Vectors	every member is an Individual NWP model	computation of different processes inside one NWP model kernel
Application of the perturbations	random simulations to form probability density function (PDF)	differences are generated from perturbation of the initial conditions (analyse)	differences are a result of covariance error matrices of initial conditions	models as well as initial conditions are different	perturbations of the initial conditions and physical and dynamic processes inside the NWP model
No. of members	limited	limited	computationally limited	unlimited	unlimited
Definitions and recognition of the differences	all differences are random and not unique	can be defined statistically but are not unique	can be defined statistically but are not unique	no differences can have a technical or physical reason	yes, well-defined
Expense (technically)	large, because of random simulation of uncertainty	reasonable because only one NWP model is required	low for small ensembles, large for larger ensembles	huge maintenance of many models is required	large, but manageable due to the maintenance, is limited to parts of the NWP model
Uncertainty validity	dependent on uncertainty simulations	predefined for example (>)3 days	predefined in error matrix for example (>)3 days	any forecast hour	the maintenance is limited to scheme performance
Applicability in intra-day	requires uncertainty computation to match time horizon	requires calibration	requires calibration	may miss extremes	parts of the NWP model
Applicability in day ahead	requires uncertainty computation to match time horizon	requires calibration	requires calibration	may miss extremes	yes
Applicability for futures (>)2 days)	yes	yes	yes	may miss extremes	yes
Deficiencies	large computational effort to create valid uncertainty	requires calibration for many applications	computationally expensive to avoid inbreeding	members deterministically tuned, extremes are suppressed, maintenance very expensive	computationally expensive

5.5.2.7 Best practices on the use of ensemble forecasts

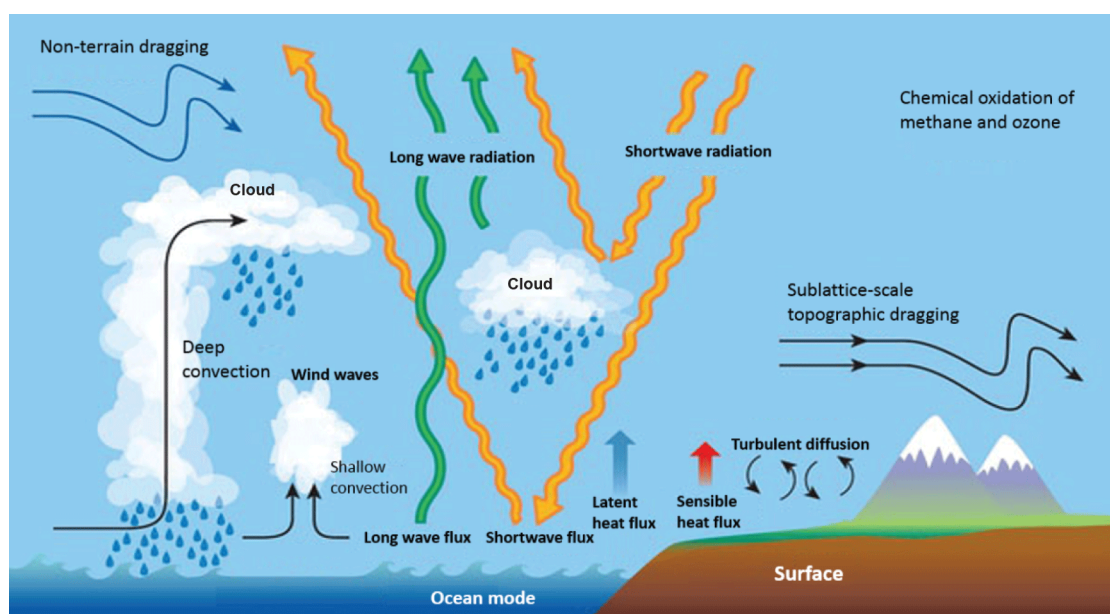
It has been scientifically demonstrated since the early 2000s that ensemble forecasting is the state-of-the-art method to find the instabilities in the atmosphere that cause most forecast uncertainty and error. Thus, it is not clear whether it is actually best practise to search for the best RMSE (or similar deterministic metric) optimised forecast, because it has become apparent that optimisation on MAE/RMSE is often against, or at least not directly in line with, the interest of the system operator and/or consumers.

Over time, it has also been found that model changes that lead to better average deterministic forecasts lack internal perturbations that seem to be required to forecast instabilities. Such instabilities are difficult to forecast and therefore it is often better not to predict them at all, if only a single value can be used and if low RMSE is the target. The likelihood of a forecast extreme coming out with an incorrect phase and thereby being hit by a double punishment of errors is high. Thus, model systems that may develop a small insignificant low, may not be punished as much as the system that tries to develop a bigger and stronger low, which may be more realistic.

In the light of the specific application in the power industry, where risks due to uncertainty in the weather development and the infeed of variable generation units have to be defined, it has to be noted that only ensemble forecasting systems have the capability to predict extremes that have not been observed in the data that is available to a statistical approach.

5.5.3 Establish regional customized forecasting model

The terrain, geomorphology, and weather types of different regions vary widely. An illustration of a parameterization schemes for sub-grid physical processes is shown in Figure 8. It is necessary to consider a combination of regionally targeted physical process parameterization schemes instead of using the same schemes for all regions (such as the simulation of physical process parameterization schemes Figure 8 shows). For wind farms located in complex topography and landforms, the grids in the horizontal and vertical directions should be encrypted as much as possible in consideration of calculation resources, and the parameterization schemes affecting the wind speed in the near-surface or boundary layer should be fine-tuned [74]. At the same time, cloud analysis should be used to assimilate satellite, radar, ground-based cloud maps, and other observational data to improve the irradiance prediction accuracy.



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Figure 8 – Illustration of parameterization schemes for sub-grid physical processes [54]

5.5.4 NWP post-processing

For the operational NWP model, the forecasting results of the same or similar weather types are often very close, and the systematic deviations under the same weather type occur repeatedly. Based on the amount of measured meteorological observation data, a statistical post-processing correction module for the prediction model can be established—that is, the wind speed and irradiance forecasting results can be statistically revised based on the error analysis and the diagnosis of the current weather situation combined with statistics methods such as MOS and machine learning, etc. The MOS method generally achieves an effective bias correction after several years of data training, but its disadvantage is that the correction effect on short-term weather changes is not ideal. Kalman filtering is a machine learning method. It is a dynamic adaptive regression optimization process that requires only a small number of data samples and a short training period to quickly adapt the weather processes, seasonal changes and the upgrade of the NWP model. It is especially suitable for the boundary layer area where the new energy site is located. However, the disadvantage of Kalman filtering is that the bias correction of extreme events and rapid error changes is not ideal.

Machine learning methods are developing rapidly for statistics correction. IBM has used machine learning methods to make cloud cover forecasting, and the results accuracy has been superior to any model [75]. Caltech scholars consider a machine learning method based on global observation system to improve the earth system model accuracy [76]. China Meteorological Administration has applied a random forest based machine learning method to make bias correction and optimize a group of forecasts (including EC, NCEP, China T639 and Japan RJTD model), and the precipitation forecast error is globally reduced compared to the single model [77]. In 2017, ECMWF met for the topic of greyzone in modelling and forecasting [78]. This greyzone is referring to the area where traditional deterministic dynamics fails, including long/short wave radiation, convection, clouds and micro-physics, atmospheric composition, boundary layer, turbulence, etc. This greyzone may be lit up by machine learning methods in the future.

In addition, dynamic diagnostic tools such as CALMET, WAsP, and WindSim can be used to correct the wind speed change caused by micro-topography through the acceleration factor. The terrain resolution of these diagnostic modes is generally tens to hundreds of meters. The magnitude, using linear or nonlinear hydrodynamic wind field calculation methods, can effectively reduce the wind speed error caused by micro-topography.

5.6 Summary

Clause 5 focused on NWP technology applicable to RPF. The basic concept of NWP was introduced. The main characteristics of NWP that are suitable for RPF, including spatial resolution, time resolution and forecast duration, etc., were then described. Clause 5 also analysed the causes of NWP error and its impact on RPF error. The progress of NWP technology (for both global and regional model) was summarized before describing the methods to improve regional models and forecasting accuracy, including assimilation and RUC method for initial condition improvement, ensemble forecasting method for reducing the uncertainty, customized model method for localization, statistical and dynamic post-processing method, etc. As these models are important components of the overall system, it is important to understand the current state and areas where improvements may occur.

6 Statistical methods

6.1 General

Statistical forecasting techniques are applied to a very wide range of forecasting problems, and the forecasting of wind and solar power production are among them. Many textbooks have been published that supply an overview of statistical forecasting techniques [79], the details of specific methods [80] and the application of statistical methods to atmospheric forecasting problems [81]. A number of methods have been applied for short-term RPF. Clause 6 provides a high-level overview of the most widely applied methods in wind and solar power forecasting and how they are typically applied.

6.2 Methods

There are two fundamental types of statistical tools applied in forecasting applications: (1) data pre-processing methods and (2) deterministic or probabilistic forecasting model generation (training) and application techniques.

In forecasting applications, data pre-processing tools serve several functions. These include the identification and elimination of erroneous or inconsistent data (i.e. quality control), handling of missing data elements, normalization of the data and the possible grouping of data into categories or classes to facilitate the construction of better forecasting models. The grouping methods include approaches such as principal components analysis (PCA) and clustering techniques. Some of the most advanced forecasting model generation techniques implicitly incorporate data grouping concepts into the forecasting model training process and therefore the value of performing explicit grouping as a pre-processing step is somewhat dependent on the method subsequently applied to develop a forecasting model.

An enormous number of forecasting model generation techniques have been formulated, tested and widely applied in operational forecasting applications. Many of these have been and are being applied in renewable generation forecasting activities. The performance results from a wide range of wind forecasting applications indicate that no single method consistently exhibits the best performance although a small set of advanced methods have produced models that are consistently among the best performers.

One of the oldest and most basic statistical forecasting methods is linear regression. Typical applications employ multiple predictor variables. The use of linear regression with two or more predictor variables is widely referred to as multiple linear regression (MLR). MLR is extensively documented in most textbooks on basic statistical methods [81]. Many variations of MLR have been formulated. Although MLR generally does not perform as well as many of the recently formulated advanced forecasting methods when large high-quality training datasets are available, it is still a valuable tool in many situations when only limited amounts of data are available. However, the coupling of MLR with the application of sophisticated data pre-processing tools can sometimes achieve forecasting performance levels that are similar to the most advanced forecasting methods.

Another set of basic empirical forecasting methods that have been employed for many years is based on the analog concept. The analog approach has implicitly been widely applied by human forecasters throughout history by noting that a particular situation is “similar” to a set of previous scenarios and therefore the outcome of the previous scenarios can be applied as the basis for a forecast for the current situation [71]. Prior to the economic availability of high levels of computing power, this approach was generally subjectively employed with graphical displays to facilitate subjective pattern matching. However, the recent availability of high-performance computing has enabled this forecasting concept to be used in a more rigorous and quantitative manner. For example, it has been applied to the WPF under the name of “analog ensemble” (AE) by Monache et al [82]. This approach basically performs a search through the available historical records to find the cases that most closely match the current forecast situation based on a set of matching variables. The historical cases that most closely match the current situation based on a specified threshold value for a closeness parameter are identified and the outcomes of those cases are used to construct an ensemble of outcomes (i.e. the “analog ensemble”). A deterministic forecast can be created by constructing a composite of this ensemble and a probabilistic forecast can be constructed by generating a probability density function from the distribution of the ensemble members. The fundamental strength of the AE approach is that it essentially creates a custom grouping of historical cases based on each forecast situation. One of the key issues with this approach is that it does not have a basis for the forecasting of cases for which there is no satisfactory match in the historical sample. Other issues are the specification of the matching variables and the definition of closeness.

A relatively recent advancement in the regression concept that has been applied for WPF applications is support vector regression (SVR). The SVR method [83] is rooted in the support vector machines (SVM) concept [84], which originated as a tool for classification problems. SVMs are supervised learning models with associated learning algorithms that analyse data and recognize patterns. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

SVR was proposed by Drucker et al [85]. SVR is the SVM tool that is most commonly applied for WPF applications. The key attribute of SVR is that its model training and optimization process utilizes a forecasting error margin (a band) to reduce the importance of data points with small forecasting errors in the training process. In other words, it places more weight on the minimization of the errors that are beyond the margin. An example of the use of SVR in a time-series-based wind power forecasting scheme is provided in [86].

One of the advanced forecasting methods that has a long history of use in forecasting applications is artificial neural networks (ANNs) [80], [87]. ANNs are a family of statistical learning models inspired by biological neural networks (e.g. the central nervous systems of animals). ANNs are generally presented as systems of interconnected "neurons" which send messages to each other. Mathematically, neurons accept inputs and have an activation function that determines their output. The connections have numeric weights that can be tuned based on experience, making ANNs adaptive to inputs and capable of learning [77]. A common formulation of ANNs that is employed in WPF applications is the multi-layer perceptron (MLP) [80]. The MLP is a class of feed-forward ANNs that consist of at least three layers of nodes. ANNs can be very powerful tools for building complex forecasting models. However, their exceptional ability to model complex nonlinear functions also makes them prone to overfitting relationships in training datasets and thus producing forecasting models that do not generalize well. This is especially an issue in noisy and small datasets (relative to the number of predictor variables and neurons in the ANN). An example of the use of ANNs in wind power forecasting is given in [88].

In recent years a considerable amount of research and development effort has been focused on the application of the decision-tree concept [88], for the training of forecasting models. Tree models in which the target variable can take a discrete set of values are called classification trees. In these tree structures, leaves represent class labels and branches represent conjunctions of features (predictors) that lead to those class labels. Decision trees in which the target variable can take continuous values are called regression trees. The term classification and regression tree (CART) is an umbrella term first used by Breiman et al [89], to refer to both of the above procedures. Trees used for regression and trees used for classification have some similarities – but also some differences.

Many of the best performing tree-based techniques construct more than one decision tree and are often referred to as ensemble methods. One class of tree-based ensemble techniques is called "boosted trees" and these methods iteratively build an ensemble by training each new instance to emphasize the training instances previously mis-modelled. A second class of tree-based ensemble techniques is referred to as "bootstrap aggregated" (or bagged) trees. This approach builds multiple decision trees by repeatedly resampling (with replacement) the training data and then constructing a composite of the results of the ensemble of trees to produce a forecasting.

One method based on the decision-tree-ensemble approach that has seen considerable use in WPF is called "random forests" (RF). RF falls into the previously noted class of methods called bootstrap aggregated trees. It operates by constructing a multitude of decision trees at training time, and for the regression application the forecasting is the mean of the forecasting of the individual trees. The algorithm for inducing a random forest [90] was developed by Leo Breiman and Adele Cutler and they created the name "random forests". The subsampled ensemble approach used in RF corrects for the tendency of decision trees to overfit their training set. An example of the application of RF to WPF is provided in [91].