



ADVANCES IN ENERGY SYSTEMS

The Large-scale Renewable
Energy Integration Challenge

Editors

Peter D. Lund • John Byrne
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WILEY

Advances in Energy Systems

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The Large-scale Renewable Energy Integration Challenge

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Preface

The global energy system confronts huge challenges in the coming decades. The present-day fossil-fuel-based energy production, which dominates the energy scenery, needs to be replaced by clean energy options to meet the climate change mitigation targets set in Paris in December 2015. At the same time, the demand for energy continues to grow, mainly due to growing prosperity in the less developed world. One of the main challenges will indeed be to secure a clean energy path to the future in the emerging economies, unlike the industrialized countries in the past.

Although global carbon dioxide emissions have increased almost by half since the days when the first climate agreement, under the UN auspice, was established in the 1990s, positive news is starting to emerge. In recent years global CO₂ emissions have been stabilized, but these now need to be sent on a declining trajectory. Much of the positive development can be contributed to the rapid market share of renewable energy sources, notably solar and wind power. The cost of these technologies is becoming competitive with their fossil counterparts. More importantly, future prospects for renewable energy technologies are bright: there still remains potential for major technology developments, efficiency improvements, and cost reductions, which together could make renewable energy the mainstream energy solution.

Indeed, respected energy scenarios, for example those developed by the International Energy Agency (IEA), indicate that in the power (electricity) sector, which is of utmost importance with respect to emissions, a significant share of future generation capacity investments will be concentrated in solar and wind power by the middle of this century. We are already witnessing that these variable renewable electricity forms deliver a major share of the national electricity supply in some countries, such as Denmark, Germany, Ireland, Italy, and the United Kingdom. In the long-

term, more countries are envisioned to satisfy their clean energy demands through renewable energy.

Although renewable energy may play an important role across the entire energy system, it is particularly in the electricity sector where the new technologies will play a dominant role. Moreover, electricity demand is growing much faster than primary energy demand, due to electrification within our societies and everyday life, which stresses the role of electricity in the future energy system. Inherently, most new renewable power production technologies, such as solar and wind, but also marine power, do not rely on a supply of fuel, meaning that their instantaneous power production depends on the prevailing and time-varying weather conditions. Thus, when transitioning to large-scale deployment of renewable energy from variable sources, a key challenge will be matching supply of power against demand, on a range of time scales from seconds to hours, days, and weeks.

Large-scale renewable electricity schemes in conjunction with existing energy systems can cause a range of different systemic issues, which need to be solved to make the best use of clean energy. Bridging the “new” and “old” energy is necessary, and both will need to coexist for some time, although the share from renewable sources will increase. An energy transition cannot be an on–off change, where we switch from old to new overnight! Integration of renewables into the energy system will thus be a critical issue, and of growing importance, in the coming years. We claim here that integration, in broad terms, will actually be the new hot topic in energy, if it is not already, which is not only linked to innovative technology solutions but which will also reshape energy markets, challenge existing business models for companies, and even integrate the consumer in a pivotal role.

Energy system integration of renewable energy is a wide field which covers themes ranging from

modifying existing energy systems to better match renewables characteristics, introducing new flexibility measures and the evolution of energy-limited technologies, exploiting communications and IT advancements within a smarter grid, and reforming markets, incentives, regulation and policy frameworks to obtain an operational, robust and economically viable energy resource portfolio.

The energy transition ahead is a huge challenge to all market actors. No one will be left untouched: policy makers, energy planners, businesses, developers, academia, and even end users need to be re-educated to understand the new rules of the game. This book aims to provide timely guidance on how to prepare for the turbulence, which rushes toward us, presenting implementable solutions and proposing successful pathways moving forward.

This book addresses the key areas of large-scale renewable energy integration and provides an authoritative overview on both the challenges and potential solutions. The book discusses the system challenges associated with renewables, grids, flexibility options, and markets, which encompass the central “integration” themes. The book is a collection of 32 authoritative contributions from specialists in the

relevant disciplines. Through this collective push, our aim is to offer the reader a fresh and skillful insight to the multidisciplinary topic.

The original inspiration for the book came through the publisher, when John Wiley & Sons established the *Wiley Interdisciplinary Reviews: Energy and Environment* journal, which mainly publishes review-type articles in energy and environment. Mr. Tony Carwardine, now retired from Wiley, suggested selecting collections of articles from the journal to create reference works in topical areas. The first book published in this manner was *Advances in Bioenergy – The Sustainability Challenge* (ISBN 9781118957875) in 2016. *Advances in Energy Systems – The Large-scale Renewable Energy Integration Challenge* is the second book in this series.

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PART I

**ENERGY SYSTEM
CHALLENGES**

Handling Renewable Energy Variability and Uncertainty in Power System Operation

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Concerns about global warming (greenhouse-gas emissions), scarcity of fossil fuel reserves, and primary energy independence of regions or countries have led to a dramatic increase of renewable energy sources (RES) penetration in electric power systems, mainly wind and solar power. This has created new challenges associated with the variability and uncertainty of these sources. Handling these two characteristics is a key issue that includes technological, regulatory, and computational aspects. Advanced tools for handling RES maximize the resultant benefits and keep the reliability indices at the required level. Recent advances in forecasting and management algorithms provide a means to manage RES. Forecasts of renewable generation for the next hours/days play a crucial role in the management tools and protocols of the system operator. These forecasts are used as input for setting reserve requirements and performing the unit commitment (UC) and economic dispatch (ED) processes. Probabilistic forecasts are being included in management tools, enabling a move from deterministic to stochastic methods, which lead to robust solutions. On the technological side, advances to increase mid-merit and base-load generation flexibility should

be a priority. The use of storage devices to mitigate uncertainty and variability is particularly valuable for isolated power systems, whereas in interconnected systems, economic criteria might be a barrier to invest in new storage facilities. The possibility of sending active and reactive control set points to RES power plants offers more flexibility. Furthermore, the emergence of the smart grid concept and the increasing share of controllable loads contribute with flexibility to increase RES penetration levels.

INTRODUCTION

The integration of renewable energy sources (RES) in a generation portfolio conveys several benefits, such as a reduction in greenhouse gases emissions and in the country's dependency on imported energy, and it decreases spot prices. However, generation from RES (i.e. wind, solar, hydro, wave, geothermal, and biomass) can be variable and uncertain, in contrast to conventional generation (e.g. coal thermal plants, combined and open cycle gas turbines). Nevertheless, many power systems have had hydropower for a long time in their portfolio, and system operators (SOs)

already have appropriate procedures for its utilization regarding the need to manage its variability and uncertainty. Note that hydropower is more flexible than other RES (such as wind and solar), in particular power plants with a reservoir. The installation of pumped storage units also facilitates water management. Conversely, geothermal generation is invariable, which might create problems because it is incapable of following load variations. The variability of hydropower, biomass, and geothermal is more apparent on yearly and seasonal timescales (run-of-river hydropower can also present daily variability), whereas the variability of wind and solar covers all timescales (including daily, hourly, and minutes variability).

At present, the penetration of wind and solar generation in many power systems has attained a high level, and this has created new challenges when operating the power system. In order to meet these challenges, the state-of-the-art encompasses new technological and computational advances for dealing with the variability and uncertainty of RES, particularly regarding wind and solar generation, since hydro variability has for a long-time been tackled in power systems.

New forecasting and decision-aid algorithms, including stochastic information, can improve the ability of a power system to cope with variable and uncertain generation coming from RES, without excessive extra operational cost while maintaining reliability standards. On the technological side, new technological advances to enhance the flexibility of conventional power plants (namely, base-load and mid-merit units) are essential. Primary frequency control provided by new RES power plants or the use of storage devices are also relevant research areas.

This article describes developments in several interdisciplinary topics related with managing high penetrations of solar and wind, and points toward research trends for the next years. First, the challenges introduced by RES (in the remainder of the chapter only wind and solar are considered) in power system operation are discussed. Then, an overview of the advances in renewable energy forecasting is presented. Renewable energy forecasts are an important input to methods for setting reserve requirements, defining the commitment schedule and performing congestion detection, which are reviewed. Consideration is also given to the electricity market role and the value of storage devices for interconnected and isolated systems. On the technological side, the importance of flexibility (from conventional generators and storage units) in power system operation is described, and some challenges and technological solutions unrelated to resource variability are reviewed, and the capability of active and reactive power control is analyzed.

THE CHALLENGES OF RES IN POWER SYSTEM OPERATION

Main Challenges

The intrinsic variability and uncertainty of RES create several challenges in power system operation and planning^[1]. At every instant, generation must follow load variations in order to maintain the generation-load balance. The variable nature of RES (e.g. rapid generation ramps) represents a challenge, in particular, for systems without hydropower, as it introduces variations in the generation side that can only be smoothed within the physical constraints of the conventional power plants (e.g. ramping up and down, minimum generation limits). In general, the available ramping rates of flexible generation units and fast-starting units (e.g. hydropower) are used for accommodating this variability. Technological solutions such as control schemes for wind power active and reactive power set points smoothen the impact of variability. For example, a dispatch center for RES with the ability to control the active and reactive power output was created in Spain^[2].

RES uncertainty also creates imbalances between generation and load as it is not possible to know (with certainty) the RES generation levels for the next hours/days. These imbalances originating from forecast errors are handled with additional generation capacity (which is an ancillary service). Computational algorithms such as forecasting algorithms and large-scale stochastic optimization (instead of deterministic tools/rules) have been developed for including information about uncertainty in the decision-making processes. The importance of new and advanced forecasting algorithms for RES, not only for the SO but also for wind power producers (in particular when trading wind power in the market), is shown by the proliferation of companies that sell this service^[3]. Storage units can also play an important role in handling RES variability and uncertainty on different timescales.

If these new solutions are not adopted, variability and uncertainty of RES could lead to situations with high operational cost. For instance, curtailment of renewable generation during low load periods and the startup of expensive fast-starting units lead to a cost increase. Moreover, even with a perfect forecast for the next hours/days, it is necessary to schedule flexible generation units for accommodating the generation ramps.

Ela and O'Malley^[4] presented a simulation framework for assessing the impact of wind power variability and uncertainty on several timescales. The results showed that the imbalance impacts increase with longer dispatch resolutions (ranging from five

minutes to one hour) and with installed wind power. Assessment of the uncertainty impacts lead to the following conclusions: the uncertainty impact increases with the forecast error, but it is not significant until the forecast error reaches a threshold; large forecast errors have a significant impact on the generation costs and branch congestion of day-ahead scheduling, but not in the real-time dispatch.

The next subsection discusses challenges and solutions for aspects unrelated to variability and uncertainty of the resource (e.g. wind and solar). Nevertheless, situations with wind turbine tripping following voltage dips are a source of uncertainty and variability to the system, but they are essentially technological and not related with the natural resource.

Other Challenges and Technological Solutions

Specific technological characteristics of RES conversion systems, which do not depend on resource variability, bring also new operational challenges as integration levels increase. There are many important ancillary services traditionally provided by conventional thermal or hydro-based generation units, such as voltage and frequency control. Additionally, conventional generation units intrinsically provide inertia to the system, which is a fundamental characteristic in order to ensure its stability. The large-scale integration of RES naturally displaces conventional generation units, thus strongly affecting ancillary services provision and global system security as a result of a general degradation of adequate frequency response^[5].

This has led SOs to define very restrictive rules and conditions for allowing increasing RES integration, which are referred to as grid codes^[6]. In general, existing grid codes require wind farms to withstand several disturbances and to support network stability through the provision of ancillary services similar to those provided by conventional synchronous units. Focusing on international grid code requirements for wind power integration, they can be generally organized in five main categories: (i) fault ride-through (FRT) requirements, (ii) active and reactive power responses following disturbances, (iii) extended variation range for voltage-frequency, (iv) active power control or frequency regulation support, and (v) reactive power control or voltage regulation capability.

From a technological point of view, energy converter manufacturers have been actively responding to SO operational requests through the development of innovative conversion systems, where the controllability and flexibility of power electronic interfaces have been assuming an increasing role^[7, 8].

The large-scale penetration of non-FRT-compliant units may lead to significant amounts of generation tripping, thus compromising system security. In order to overcome these difficulties, system operators defined specific requirements that all generators should fulfill in order to be connected to the grid^[9]. These requirements are generally specified in a voltage-time curve that defines the region in which generators are not allowed to trip. As an illustrative example, Figure 1.1 depicts a general shape of the voltage-time curve where the points A–H define key time-voltage values delineating the region in which wind generators should remain connected to the grid during low-voltage periods. The values shown in Table 1.1 illustrate different parameterizations of the voltage-time curve for different SOs, which reflect specific grid characteristics in terms of generation units and protection philosophies.

More recently, interest in large photovoltaic (PV) plants has gaining additional attention. Therefore, specific control requirements for photovoltaic inverters regarding FRT capabilities and voltage control are beginning to become a research topic, which will be developed in the near future^[10].

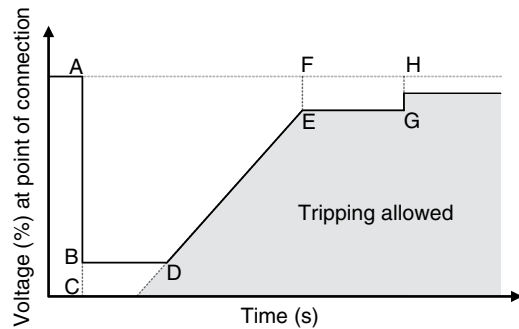


Figure 1.1 Generic FRT voltage versus time characteristic curve.

Table 1.1 FRT voltage and time values for European grid codes.

Grid Code	BC	BD	AF	FE	AH	HG
Denmark	25%	0.1 s	0.75 s	25%	10 s	N.A.
Germany	0%	0.15 s	0.15 s	30%	0.7 s	10%
Ireland	15%	0.625 s	3 s	10%	N.A.	N.A.
Spain	20%	0.5 s	1 s	20%	15 s	5%
Spain (Canary Islands)	0%	0.5 s	1 s	20%	15 s	5%
United Kingdom	0%	0.14 s	1.2 s	20%	2.5 s	15%
Portugal	20%	0.5 s	1.5 s	20%	10 s	N.A.

The consequent displacement of synchronous generators affects power system inertia and primary frequency control capabilities, limiting further integration of RES. In order to overcome such limitations, the possibility of endowing wind energy converters with additional control loops in order to provide either inertia emulation capabilities and primary frequency regulation has been discussed^[8, 11]. The general approach is to operate RES with a certain reserve margin through the appropriate use of deloading mechanisms. Thus, the reserve margin can be autonomously deployed in case of frequency deviations through the use of a power reference-frequency droop control.

Additionally, a supplementary control-loop based on the rate of change of the frequency deviation enables RES to emulate an inertial response. Similar operational characteristics are being envisioned for large offshore wind farms connected to a mainland grid through multiterminal high-voltage direct current grids^[12]. Energy storage systems can also provide an important contribution to primary frequency control, namely, in island systems^[13], but also in interconnected systems^[14].

ADVANCES IN RENEWABLE ENERGY FORECASTING

During the last 15 years, research work has been conducted on developing forecasting algorithms which achieve a forecast error reduction and an expansion of forecasting products^[3]. Furthermore, the number of companies selling forecasting services for RES has proliferated, and the reliability and availability of their service has improved. Presently, SOs use forecasts in their daily operation, embedded in decision-making processes^[15]. Research on wave energy forecasting is also being conducted^[16], although this technology is not at the maturity levels of wind and solar technologies.

At a regional/national level, wind power forecasting (WPF) literature reports a normalized mean absolute error (NMAE) of around 6–10% and a normalized root mean square error (NRMSE) of around 8–12% of the installed capacity for 24 hours ahead, rising to 11–14% and 14–17% for 48 hours ahead^[3]. For solar power forecasting (SPF), the NRMSE is around 4.3–4.9% for day-ahead forecasts^[17]. The load forecast error is generally measured as a mean absolute percentage error and its value is around 1–2% for 24-hours ahead forecasts^[18]. Note that the real impact of the RES forecast errors can only be measured by an increase in power system operating costs (e.g. increased use of reserves for balancing forecast errors).

Wind Power Forecasting

In general, SOs only need WPFs for a horizon up to 3 days ahead. This time horizon can be divided into two classes^[3]: (i) very short term, for a maximum of 6 hours ahead with different time steps (10, 15, 30, and 60 minutes), (ii) short term, for a maximum of 72 hours ahead in 30 and 60 minute time steps. The algorithms used to produce a WPF for these two horizons can differ in type and input data.

Forecasting algorithms for very short-term horizons use as input past values of the time series. Classic examples are models based on the autoregressive integrated moving average^[19], but recently, regime-switching models^[20], such as Markov-switching autoregressive, are being used for capturing the influence of some complex meteorological variables on the power fluctuations. Furthermore, the combination of dispersed meteorological on-site and off-site observations and mesocale numerical weather predictions (NWP)^[21] can lead to significant improvements in very-short-term horizons^[22].

Forecasting algorithms for a short-term horizon require NWP data. Several statistical and machine learning algorithms have been applied for converting the forecasted meteorological variables into wind power generation forecasts^[3]. The use of cost functions for fitting prediction models under non-Gaussian errors^[23], as well as the combination of different statistical and NWP models^[24], can improve accuracy.

In addition to research work seeking a forecast error reduction, different forecasting products have been developed: regional forecasts, uncertainty forecasts, and ramp forecasts. These forecasts are inputs to the power system management algorithms reviewed in the following sections.

Regional (or aggregated) forecasts, resulting from a process called upscaling, consists of estimating the total wind power, using information from forecasts of representative wind farms, for which NWP and/or online observations are available^[25]. This process is justified when the observations from some wind farms are unavailable or the data quality is poor. From the literature, it is known that the aggregation of wind farms reduces the forecast error because of spatial smoothing effects^[26].

A point forecast does not give any information about the errors associated with the forecasted value. This motivated the development of advanced physical and statistical methods for estimating and communicating wind power uncertainty. This uncertainty can have different representations: probabilistic, statistical, and meteorological-based scenarios.

In the literature, a broad set of statistical methods for producing probabilistic WPF can be found, such as local quantile regression^[27] or conditional kernel density estimators^[28]. The probabilistic forecasts can be expressed as a set of quantiles or interval forecasts (as depicted in Figure 1.2a), or a probability density function (*pdf*), or moments from the distribution. However, the forecasts produced by these methods do not include the temporal and spatial dependency of the forecast errors. The dependency of the errors is valuable information for time-dependent decision-making problems, such as storage management^[29] or UC^[30]. The state-of-the-art in WPF represents this time dependency by scenarios that are time/spatial trajectories or random vectors (as depicted in Figure 1.2b).

The scenarios can be statistical or physical based. Statistical-based scenarios are generated with simulation techniques that sample random vectors using a dependency structure (e.g. covariance matrix) capturing the temporal/spatial dependencies of the forecast errors. Pinson et al.^[31] described a method for sampling random vectors from the forecasted marginal cumulative probability functions. The method uses a multivariate Gaussian distribution where the covariance matrix represents the temporal dependency between the forecast errors. This method can also be extended to include spatial dependency^[32].

Physical-based scenarios (or meteorological ensemble) capture two different sources of error: initial conditions and the model (i.e. representation of the dynamics and physics of the atmosphere). These scenarios are obtained with three approaches: (i) different initial conditions or numerical representations of the atmosphere are used in each run of the NWP system^[33]; (ii) outputs of different NWP forecast models or from the same NWP model with different parameterizations; (iii) different forecasts made at different times with the same NWP model^[34]. These NWP ensembles can be converted to wind power scenarios^[35].

Recently proposed, a different type of scenario is associated with spatial fields^[36], which are statistically transformed NWP points from a grid covering the wind farm to an equivalent value representing the surface roughness and terrain at a chosen reference point for the wind farm location. Compared with other uncertainty representations, NWP spatial fields capture phase errors in NWP and sampling errors^[37].

Finally, although the scenarios already capture ramps and extreme weather events, another forecast product is ramp forecasting^[38]. A ramp forecast provides information (point and probabilistic) about the magnitude and timing (i.e. phase error) of future wind power rapid variations. Bossavy et al.^[38] used

a filtering/thresholding approach for detecting and forecasting ramps using, as input, forecasts produced with meteorological ensembles. The forecast gives the probability of observing a ramp within a set of time intervals. Ferreira et al.^[39] presented a different methodology also based on a high-pass filter and using statistical scenarios as inputs.

Solar Power Forecasting

Although research on WPF has reached a maturity level, research on SPF could be classified as “under development.” In contrast to WPF, SPF requires specific forecast models for the different technologies, such as concentrated photovoltaic and concentrated solar thermal. Nevertheless, current research is more concentrated on the weather forecasting side.

Differently from WPF, pure statistical models with past observations can produce SPF with an acceptable quality for hours/day-ahead horizons with hourly time steps^[40]. The main reason is that the serial dependency presents a strong daily and weekly seasonal pattern. In fact, the daily cycle of solar irradiation is rather easy to predict. Nevertheless, as ‘shown’ by Ahlstrom and Kankiewicz^[41] and depicted in Figure 1.3, intrahourly forecasts present a high variability caused by clouds. In fact, clouds are the main cause of short-term variation, and clouds of different types, speed, and size represent different impacts in solar power generation.

Heinemann et al.^[42] identified different input data sources for the various time horizons of interest. For very short-term horizons (between 30 minutes and 6 hours), the authors suggest the use of satellite-based cloud motion vector fields. For short-term horizons (up to 2 days ahead), the forecasts should be based on NWP data.

Heinemann et al.^[42] describe very short-term forecasting algorithms based on cloud-index images that are predicted with motion vector fields^[43] derived from two consecutive images. For short-term horizons, the authors forecast surface solar irradiance with a NWP mesoscale model. The results showed a good accuracy for clear sky situations, but with broken clouds and overcast conditions, the error increased significantly. A second approach described by the authors is to use a mesoscale NWP model to predict variables describing cloudiness, and this information is converted to solar irradiance. Wittmann et al.^[44] examined the importance of combining NWP and aerosol-based forecasts for day-ahead horizons. According to the authors, aerosol information is of great relevance for clear sky situations, which are the most frequent situations at solar farm locations.

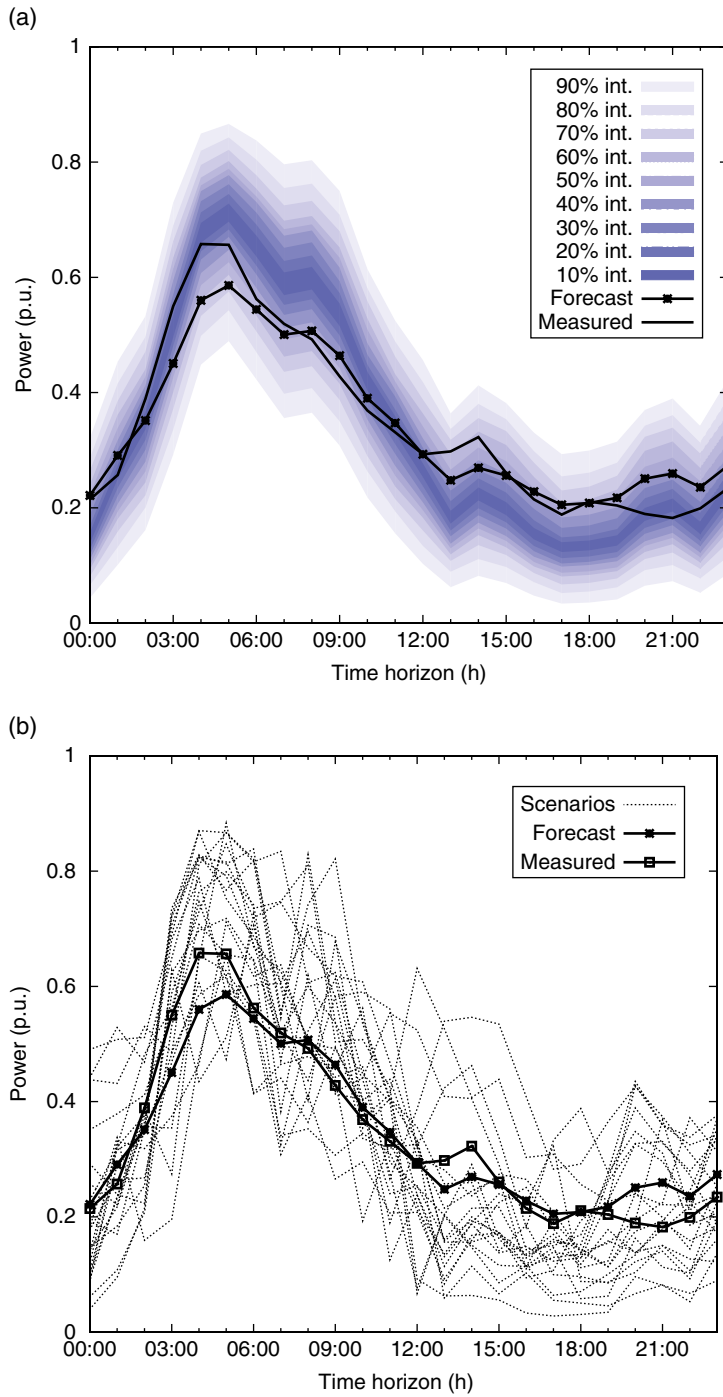


Figure 1.2 (a) Forecast intervals, centered in the median, and limited by their lower and upper bounds, which are forecasted quantiles. (b) Twenty statistical-based scenarios with temporal dependency of errors that respect the marginal distribution of the probabilistic forecasts (i.e. plot in (a)).

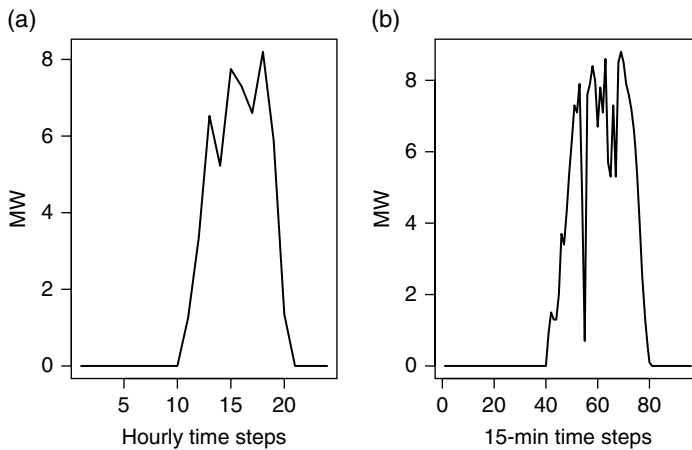


Figure 1.3 Generation variability of solar power due to clouds: (a) hourly average; (b) 15 minute average.

Lorenz et al.^[45] showed that, as with wind farms, the aggregation of photovoltaic (PV) panels and farms decreases the forecast error, by smoothing the cloud effect. A forecast model for a regional forecast is also described^[17].

Finally, note that most statistical-based uncertainty forecasts techniques from WPF can be applied to this problem. Furthermore, meteorological ensembles also have a potential application in SPF.

THE IMPORTANCE OF GENERATION FLEXIBILITY

In the past, flexible power plants were mainly used for handling load variability and uncertainty. RES introduces variability and uncertainty in the supply side, and with a higher magnitude in a scenario with high RES penetration. The wide regional distribution of multiple RES power plants decreases the variability and uncertainty of RES-based generation^[1, 26].

The flexibility of the power plants can be defined as the ability to react (i.e. modify generation levels in response to a command from the SO) quickly enough to rapid generation/load ramps and to deviations between scheduled and realized values. Generation flexibility is characterized by several parameters, such as ramp rate (% of MW per minute), technical and economic minimum generation level, start-up and shut-down time. Lannoye et al.^[46] propose a methodology to compute the Insufficient Ramping Resource Expectation index, which is a metric that measures power system flexibility for long-term planning studies.

The following separation between power plants can be made^[47]:

- *Peak units* are able to start, shutdown, or change their generation level very quickly in response to a command from the SO. Units of this type can handle minute-to-minute variations and uncertainty, and some examples are open-cycle gas turbines and hydropower plants.
- *Mid-merit units* have the ability to ramp up to their maximum power and down to their minimum, but are slower than the peak units. Examples of these units are combined cycle gas turbines (CCGT) and biomass, and they cover interhour variations and uncertainty.
- *Base-load units* have slower response times and normally operate across the entire day or during predefined periods. Units such as coal-fired plants, nuclear, and geothermal might require around six hours to start or provide a flexible response. These units can provide some flexibility for daily variability.

In addition to these three categories, there are also must-run units that ensure the dynamic stability of the power system (e.g. minimum online inertia in the system). The minimum generation level of these units may be a critical factor during periods with high penetration of RES.

In some cases, such as France and Germany, nuclear power plants can also provide load-following capabilities^[48]. However, this has economic costs, mainly related with the load factor, as it is only profitable if operating at high load factors (i.e. above 90% of rated power). Furthermore, coal- and gas-fired power plants are becoming more flexible with recent technology. For instance, in Germany, older coal power plants have ramp rates of 2%/minute, whereas new plants have rates of 4–6%/minute^[49].

A critical limitation is the minimum load limit of conventional generation units (both technical and economic), which, in general, is around 40–50% of the rated power. Nicolosi^[50] reported a lower flexibility in the German power system for the period between October 2008 and December 2009. In situations with generation surplus, all the generation sides together were unable to reduce the generation below 46%, in particular the base-load technology, which showed high minimum generation levels (due to technical and economic constraints). Soder et al.^[51] reported that the Portuguese power system was able to accommodate a very high wind power penetration level (maximum of 81% at 6:45 a.m.) by stopping several hydropower plants between 0 and 4 a.m., and only one gas-fired plant was kept in operation at 25% of rated power. The flexibility of hydropower units and its pump storage was used to balance wind power fluctuations, and the interconnection with Spain allowed exporting generation surplus.

The cross-border interconnections also play an important role in increasing the flexibility. It facilitates the use of more flexible power plants where they are needed to balance RES. For example, a high penetration of wind power generation is feasible in Denmark because of the good interconnections with Sweden, Norway, and Germany. The interconnection with Norway provides access to its fast starting hydropower plants, which can be used as reserve capacity contracted in the NordPool electricity market^[52]. However, a higher transfer capacity between countries may also create overload problems in situations with high RES-based generation in one control area^[53]. Therefore, cross-border interconnections should be combined with suitable operational procedures (e.g. forecasting, stochastic power flows) and investment in flexible AC transmission system (FACTS).

The SO can use this flexible generation as reserve capacity, and methods reviewed in the following section optimize the use of this available flexibility.

METHODS FOR HANDLING THE VARIABILITY AND UNCERTAINTY FOR STEADY-STATE OPERATION

In the operational domain, the SO has a limited time for conducting studies and examining alternatives. The uncertainty in this domain is relatively small when compared with the planning domain, which leads the SO to analyze the current conditions by a series of deterministic methods or rules. The main problem with deterministic approaches is that the user does not know the level of risk associated with

future operating conditions. This normally leads to a conservative operation with high operating costs or to unanticipated high risk during operations. As the penetration of renewable generation increases, new management procedures and algorithms emerge for handling generation variability and uncertainty. The use of uncertainty forecasts for renewable generation becomes a relevant input for decision-aid algorithms. It is important to stress that modeling forecast uncertainty in decision-making algorithms with the average historical forecast errors (*a priori* estimation) is not the same as using uncertainty forecasts (*a posteriori* estimation) directly in the methods, and might lead to conservative and expensive operating strategies.

This section presents an overview of new management algorithms for supporting power system operation in steady-state conditions with a significant penetration of renewable generation. The majority of the methods in the literature only consider the presence of wind power in the system. Nevertheless, a generalization to other RES (such as solar) is in general possible and straightforward if forecasts for solar power generation are available.

Methods for Setting the Reserve Requirements in the Operational Domain

In each time instant, the SO is responsible for maintaining the balance between generation and load in the power system. This leads to the need for a reserve capacity composed of loads and generation units able to respond to possible problems. Upward and downward reserves are normally necessary. The upward reserve consists of generation units (or loads) online or offline able to, in a short period, increase their generation levels (or decrease their consumption levels). The downward reserve consists of online generation units able to decrease their generation levels or loads able to start consuming (or increase consumption) in a short period.

The classical categories of reserves^[54] are: primary (or frequency response), secondary (or regulation reserve), and tertiary (or replacement reserve). Primary reserve is used for stabilizing the system frequency at a stationary value after a disturbance or incident in the time frame of seconds. Secondary reserve is dispatched via automatic generation control for restoring the frequency and interarea power exchanges to their nominal values in a time frame of 15 minutes. The SO restores or supplements secondary reserve levels by manually activating tertiary reserve, in a time frame between 15 minutes and 1 hour.

High penetration levels of renewable energy (mainly wind and solar) in the system require a revision of these

reserve categories. Large shares of renewable generation do not create problems (discounting the sudden disconnection due to voltage dips), in interconnected systems, for the timescale of primary reserve^[55].

Holtinen et al.^[56] divided the reserve categories in: *nonevent* (normal operation) for variability and forecast errors inside the scheduling period; *fast event* (contingency operation) for an unplanned outage of a generator or cross-border transmission line; *slow event* for expected net-load ramps; and forecast errors that can occur on longer timescales (tens of minutes to hours). The authors argue that generation from RES does not change fast enough to be a contingency event, and the impact on secondary reserve is lower than the impact on tertiary reserve (both reserves are included in the *nonevent* category). High penetrations of RES will introduce *slow events* characterized by high rapid generation ramps and forecast errors.

On the timescale of tertiary reserve, several countries have already created a reserve category for *slow events*; for example, the manual reserve in Denmark and the balancing reserve in Spain and Hydro-Quebec.

Deterministic methods (or rules) for setting the reserve requirements have served many SOs in the past^[57], mainly because they are easier to be understood and applied by operators, and continued to high security levels with minimum study effort. However, with high levels of renewable generation, excessively conservative approaches would result in a high reserve cost and to a waste of renewable generation-related benefits. For example, operators not comfortable with the possibility of high forecast errors might define high levels of reserve to compensate potential deviations, thus reducing the economic attractiveness of RES. On the other hand, because risk is not really monitored in deterministic approaches, conservative rules may sometimes fail in specific circumstances not included in their original rationale.

The alternative consists of using probabilistic methods for setting the reserve requirements. In fact, the use of probabilistic methods for setting the reserve in the operating domain is not new. A classic example is the Pennsylvania–New Jersey–Maryland (PJM) interconnection method that evaluates the risk of the committed generation units considering generation outages and load forecast errors^[58].

The First Step: Hybrid of Probabilistic–Deterministic Rules

Presently, SOs are starting to include information about forecast errors and uncertainty when defining the reserve requirements. The first step consisted of including a probabilistic component in the former

deterministic rules. For example, Electricity Reliability Council of Texas (ERCOT) (Texas Independent SO) defines the nonspinning reserve (the one that handles forecast errors) as the 95th percentile of the observed hourly net load error from the previous 30 days, plus the size of the largest unit^[59]. The Spanish SO (REE – Red Eléctrica de España) defines the balancing reserve requirements as the sum of the generation shortage/surplus due to load and wind generation historical forecast errors, and unplanned outages^[60]. The European Network of Transmission System Operators for Electricity (ENTSO-E) revised the rules from the former Union for the Coordination of Transmission of Electricity (UCTE), and a new probabilistic criterion for setting the total reserve (secondary and tertiary) was included^[54], but without explicitly mentioning renewable generation.

The Next Step: Probabilistic Methods

Gouveia and Matos^[61] extended the PJM method by including the wind power uncertainty modeled with a Markov model. The main limitation (common to other methods) is that the model does not include forecasting information, but only the *a priori* probability distribution of a set of wind power levels. Thus, the next step is to use probabilistic tools with uncertainty forecasts as input.

The first set of methods assumed that the WPF error follows a normal distribution. Several authors^[62, 63] compute the level of imbalance between load and generation by summing the variances of the load and WPF errors ($\sigma_{LW}^2 = \sigma_L^2 + \sigma_w^2$), assuming that both random variables are normal and independent. The reserve requirement needed to deal with the estimated imbalances is given by the variation contained within three standard deviations ($3\sigma_{LW}$) of the overall system imbalance. Doherty and O'Malley^[64] presented an analytical method for defining the reserve requirements. The model includes generators' unplanned outages (both full and partial outages), load, and WPF errors modeled by a normal distribution. Ortega-Vazquez and Kirschen^[65] described a method for minimizing the sum of expected cost of energy not served (i.e. expected energy not served [EENS] multiplied by the value of lost load) and the operating cost. The wind power and load uncertainties are normal distributions and combined by summing their variances.

However, the normal distribution assumption is highly questionable because the WPF errors' distribution presents high skewness^[66] and kurtosis^[67], even when several wind farms are aggregated^[25]. This assumption, when setting the reserve requirements, may result in an underestimation of the risk^[68].

Excluding this normality assumption, Matos and Bessa^[69] proposed a probabilistic method that takes as input a probabilistic WPF. The load probabilistic forecast and generation uncertainties (i.e. unplanned outages of conventional generation units and wind turbines plus WPF probabilistic forecast) are convolved with the fast Fourier transform. From the convolution result, risk attributes related with a generation shortage (upward reserve) and surplus (downward reserve) are computed for each reserve level. The results of this exercise are risk/reserve and risk/cost curves for each lead time. As an example, Figure 1.4 depicts the EENS (one of the possible reliability indices) against the reserve level. Establishing this relation allows the SO to make a decision with different methods: (i) set a reference value for the risk and get the reserve level directly from the curve; (ii) establish a trade-off between reserve cost and risk and find the corresponding optimal reserve level; and (iii) build a value function to find the best compromise between cost and risk. Bessa et al.^[70], in the framework of the European project ANEMOS.plus, reported results from an operational demonstration of this method for the Portuguese SO. The demonstration showed that the probabilistic method outperformed the deterministic rules in use at that time.

Menemenlis et al.^[71] describe a method based on convolution which also constructs risk/reserve curves for each lead time. The wind power is

modeled with gamma functions fitted with time-varying parameters for each class of generation level. The decision method consists of establishing a reference value for the risk. The main limitation of the method is that the gamma functions for each wind farm are combined, assuming independence of the uncertainties. This assumption does not consider the spatial dependency of uncertainties, which cannot be neglected. Maurer et al.^[72] also proposed a method based on convolution, but the authors did not provide details about how the uncertainties are estimated. An interesting contribution is a two-step approach for separating the total reserve in secondary and tertiary reserve. The use of ensembles of wind power for setting the reserve was proposed by Pahlow et al.^[73] The authors, using ensembles from the multischeme ensemble prediction system^[74], compared several rules, such as reserve equal to the difference between the minimum and maximum of the ensemble in each hour. The results showed that the rules based on the ensemble are cost efficient and cover more hours when compared with the deterministic rule (i.e. 11% of installed capacity).

The reviewed methods can be used for purchasing reserve services in a sequential electricity market (i.e. reserve market after the energy market) or included in the UC market clearing process. This second possibility is reviewed in the UC section.

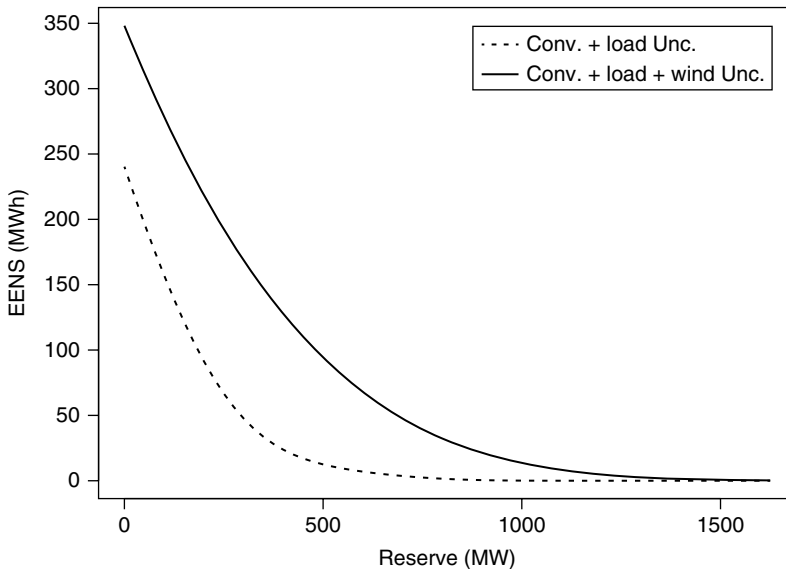


Figure 1.4 Example of the expected energy not supplied as a function of the reserve level for a look-ahead time and taking into account different sources of uncertainty: conventional and load uncertainty; conventional, load and wind power uncertainty.

Reserve for Extreme Events

The additional value/information of ramp forecasting in decision-making problems (e.g. UC) is currently under discussion. Some authors believe that information about ramps should mainly be used as supporting information for the operators, and not as a direct input to an optimization problem (e.g. UC)^[39, 75]. A ramp forecast tool can be used to generate alarms to the operator and quantify the risk, supporting preventive measures against rapid variations of wind power.

A particular type of ramp occurs in situations with high wind speed. The wind turbines have a cut-out wind speed value (generally around 25 m s^{-1}), and above that value the turbine starts to trip. In this case, the SO must deal with an unforeseen rapid drop of wind generation that must be forecasted in order to take preventive measures. Figure 1.5 depicts a wind power reduction of around 600 MW in 1400 MW telemetered by the SO of Portugal, and originated by the cyclone *Klaus* on 23 January 2009. The forecasting system did not predict this extreme event, and the incident was handled with fast starting hydro units and importing energy from Spain. With solar power generation, an equivalent event can be triggered by fast-moving clouds.

Lin et al.^[76] describe a model for estimating the wind power generation reduction under extreme wind conditions. A high-resolution tool, with calculations in the frequency domain and considering the spatial distribution of the wind farms, simulates power reduction trajectories in a minute-to-minute time resolution. From the simulation results, a reserve

requirements curve informing how much reserve is required for different wind speed values (close to cut-out speed) is constructed. In the operational domain, the tool combined with NWP enables the calculation of reduction trajectories samples and a corresponding reserve requirements curve. The main advantage of the described model is that it does not require extensive historical data of the wind farms in the region under analysis.

UC and ED with RES

The UC problem consists of scheduling generation units to minimize the cost of supplying the forecasted load with a set of constraints related to power system security and operation (e.g. ramping rates, start-up times). The economic dispatch (ED) is based on the UC generation schedule and computes the generation levels of each unit that lead to the lowest possible cost. In summary, the UC decides which units should be running (e.g. on or off) and the ED determines the generation levels of the committed (or online) units. It is common to find these two processes in noninterconnected power systems and in the United States as a market clearing instrument. The UC and ED, in the United States, are used in the following steps^[15]: in the day-ahead market clearing, a security-constrained UC and ED is used to schedule and dispatch the generation units, using bids (price and quantity pairs in a stepwise increasing function) from market agents; after the day-ahead market clearing, a reliability assessment commitment (RAC) is performed using security-constrained

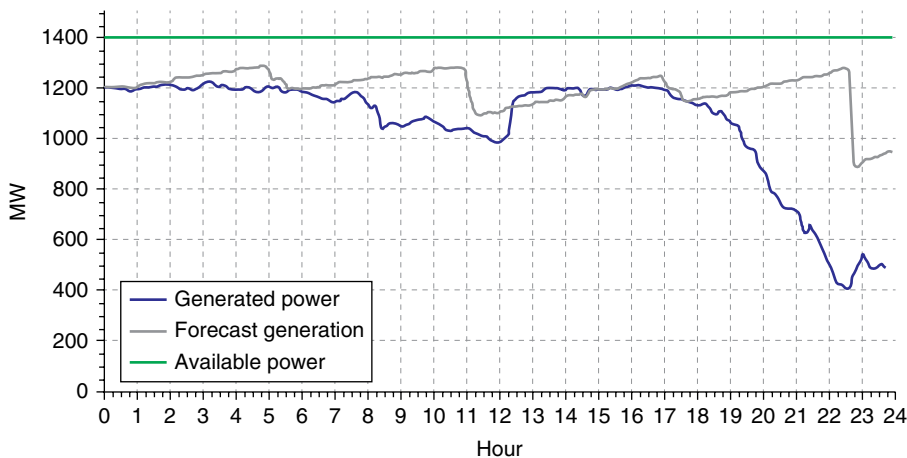


Figure 1.5 Wind power reduction in Portugal due to extreme wind speed conditions originated by the cyclone Klaus in January 2009 (the wind power generation values are only from telemetered wind farms, available in real time, and not the total wind power generation in Portugal). Source: Reproduced with permission from Ref. 131. Copyright 2009, REN.

UC; a security-constrained ED is performed in the real-time market to dispatch the units scheduled by the day-ahead market and RAC.

Presently, SOs only use deterministic UC/ED, and the load and conventional generation uncertainty is covered in a constraint for guaranteeing a fixed amount of reserve. The state-of-the-art for solving the UC problem is mixed-integer programming (MIP), which is available in most commercial optimization packages. New UC/ED policies that include probabilistic information can be promising alternatives with increasing levels of RES. For example, ERCOT, when making the day-ahead plan of the generation resources, uses as a WPF the 20% quantile (i.e. 80% probability of surplus)^[77]. This can be understood as a conservative approach that guarantees a safety margin, but increases the cost due to the overcommitment of conventional generation units and leads to a greater need for downward reserve. Thus, an alternative approach is stochastic UC/ED (SUC/SED).

The state-of-the-art for the SUC and SED is a two-stage stochastic programming with recourse^[78]. The UC decisions, excluding fast-starting generation units, are taken in the first stage (modeled as *here-and-now* variables). The dispatch decisions are made in stage 2, modeled as *wait-and-see* variables, when realized values are known (i.e. real-time).

Generally, this stochastic problem is converted into a deterministic equivalent that is solved with MIP. The objective function in the published formulations is the minimization of the expected cost^[30, 78]. However, subjects such as uncertainty modeling, strategies for including the reserve requirements, and whether or not transmission network constraints are included differ in the literature.

Uncertainty Modeling

Uncertainty is generally modeled through a set of scenarios. However, the characteristics of these scenarios differ from author to author. Some scenarios are generated with techniques that are only suitable for planning studies^[79]. For the operational domain, several authors generated scenarios assuming that the wind power follows a normal distribution and without considering the temporal dependency of errors^[80–83].

Further UC formulations use different principles. Constantinescu et al.^[84] describe a computational framework that combines a NWP model with a sampling technique for generating physical-based scenarios able to capture the spatial–temporal evolution of forecast errors. Wang et al.^[30] and Zhou et al.^[85] modeled wind power uncertainty with the method from Pinson et al.^[31] Sturt and Strbac^[86]

use a quantile-based scenario tree for wind power uncertainty. The scenario tree is constructed from a user-defined topology, and forecast errors at each node are determined from quantiles of the forecast error distribution.

The use of a large set of scenarios increases the computational requirements. A common practice is to reduce the number of scenarios with a technique that aggregates similar scenarios and eliminates scenarios low probability. The most-used techniques are backward reduction and forward selection based on a family of Kantorovich or transportation probability metrics^[87]. Pappala et al.^[82] described a scenario reduction method based on particle swarm optimization, and Sumaili et al.^[88] described another algorithm based on clustering techniques.

Modeling the Reserve Requirements

In the SUC, uncertainty is implicitly modeled by using a set of scenarios. According to Bouffard and Galiana^[81], the reserves in the SUC are defined internally and there is no need for specifying *a priori* a reserve requirement. The quantile-based scenario tree proposed by Sturt and Strbac^[86] for modeling wind power uncertainty avoids the need to consider additional reserves for the SUC. Because the scenarios capture the worst-case tail, it allows the SUC to model dynamic levels of reserve that weigh the cost of providing them compared with the load shedding cost or the cost from committing expensive generation. In the SUC of Morales et al.^[89], the reserve requirements are determined considering the value of lost load, electrical energy cost and reserve bids, and also a set of scenarios.

However, other authors also studied the inclusion of a constraint related with reserve requirements, for modeling uncertainty explicitly.

Ruiz et al.^[78], although not considering RES uncertainty, showed that the inclusion of a suitable amount of reserve requirements in the SUC formulation resulted in better performance in terms of total cost and unserved energy. Restrepo and Galiana^[90] proposed a deterministic UC that includes a constraint that limits the probability of the forecasted residual load exceeding the schedule upward and downward reserve. Wang et al.^[30] showed that an SUC with additional reserve for covering the impossibility of comprising all events in a limited set of scenarios performs better than an SUC without additional reserve. Pappala et al.^[82] in addition to a set of scenarios, considered additional spinning reserve for dealing with wind power ramps between two consecutive periods.

Stochastic Versus Deterministic UC/ED

Several authors conducted studies comparing deterministic UC and SUC. Tuohy et al.^[79] compared both approaches and the SUC decreased the total cost around 0.25%. Interesting differences were: the deterministic UC commits more expensive mid-merit gas and peaking units; the SUC imports more energy because of the scenarios with low wind power generation; deterministic UC increases the number of startups in the generation units; the SUC presents a better performance in meeting the spinning and replacement reserve requirements.

Wang et al.^[30] compared different deterministic and SUC strategies for dealing with wind power uncertainty. Results for a three-month period showed that a deterministic UC without any WPF (i.e. the wind generation is assumed to be zero) resulted in an overcommitment of conventional units, and when only point forecasts for wind power are included, it leads to the highest cost and load curtailment. The SUC strategies have a relatively low cost, but a deterministic UC with a reserve rule (point forecast minus 10% quantile and 5% of the load) obtained a similar cost. Zhou et al.^[85] extended this comparison to the RAC, where fast-starting units are committed or decommitted by using very-short-term wind power probabilistic forecasts and scenarios in the SUC. Both articles show that a dynamic rule for setting the reserve combined with deterministic UC presents a better performance than a fixed reserve value and can yield similar results to SUC, without the need to change considerably the current operational procedures or increasing the computational effort. On other hand, the SUC, as it uses scenarios with temporal correlation, can capture with more detail the ramps between hours and, consequently, compute a suitable reserve for dealing with temporal variability. Another advantage is that it includes the uncertainty impact in the objective function.

Papavasiliou et al.^[91] compared an SUC that uses scenarios with a deterministic UC with two alternative rules for setting the reserve: 20% of the forecast peak load, 3% of the forecasted load plus 5% of the forecasted wind power. The SUC improves the daily operational cost over the deterministic UC: 0.39% for the first rule, and 0.54% for the second rule with 7.1% of wind power penetration; 1.33% and 1.09% correspondingly with 14% of wind power penetration.

Lowery and O'Malley^[92] studied the impact of WPF errors statistics (i.e. variance, skewness, and kurtosis) on the UC and system operation, using a test system a portfolio from the all Island Grid study (Ireland and Northern Ireland). The authors evaluated which

statistical properties of the error distribution contribute to the system operation performance. The results showed that variance has the most impact on the total cost, and skewness only decreases the system cost if complemented by kurtosis. For instance, skewness combined with variance results in an overcommitment of expensive base-load units due to an incorrect estimation of the tail probabilities. The introduction of these error statistics in the UC changes the generation levels of flexible mid-merit and peak units, while base-load units are almost stable. Furthermore, the number of unit startup increases with the forecast uncertainty, with the exception of coal-based power plants.

The authors also evaluated the impact of over- and underestimation of these statistics, and several conclusions were obtained. For example, inaccuracy in kurtosis will aggravate the effects (i.e. system cost) of an underestimation of variance because an overestimation of kurtosis increases the dependency from flexible units, and underestimation overcommits base-load units. The overestimation of kurtosis when variance is accurate results in a decrease of the total cost because it reduces the use of slower generation units. The lowest number of require startups when variance is underestimated is when skewness is accurate. If variance is overestimated, inaccurate skewness reduce the number of startups of flexible units due to an incorrect estimation of the expected wind power.

Constrained SUC/SED

The constrained UC/ED is particularly important for countries (e.g. United States) with nodal prices. When the transmission network constraints are included, new optimization techniques are needed for solving the problem.

Wu et al.^[93] use Lagrangian relaxation to decompose the optimization problem in tractable deterministic constrained SUC subproblems that can be solved with MIP. Wang et al.^[80] divided a constrained SUC in a master problem according to the wind power scenario. The security of an initial dispatch is checked in a subproblem, and a redispatch is made for mitigating violations. If the redispatch is insufficient, Benders decomposition is used to revise the generation commitment of the master problem. Morales et al.^[89] present a network-constrained market-clearing mechanism for energy and reserve (spinning and nonspinning) optimization, considering wind power uncertainty. A two-stage stochastic programming problem is proposed. The first optimization stage comprises the constraints and rules of the electricity market, whereas the second stage represents the power system operation and physical limitations.

Managing Network Congestion

A “weak” transmission network with a high penetration of RES is prone to congestion situations, which limits the benefits arising from RES integration. For instance, network bottlenecks bind the reduction in operational costs promoted by wind power and increase the amount of curtailed wind generation during low load periods^[77, 89]. The use of power flow tools capable of including renewable energy uncertainty can help detect and manage situations with congestion, avoiding curtailment of renewable energy, and in the medium term can defer network investments.

Two approaches can be found for including uncertainty in power flow calculations: probabilistic power flow (PPF) and fuzzy power flow (FPF). Both methods calculate, under steady-state conditions, the probability distributions or fuzzy values (possibility distributions) for voltages (angle and magnitude), active and reactive power flows, and active losses.

In PPF studies, wind speed uncertainty is frequently modeled by a Weibull distribution^[94]. However, this modeling assumption is not suitable for the operational domain because the goal is to include forecast uncertainty. Moreover, the spatial dependency between the random variables is also important for power flow calculations.

The first PPF considering WPF uncertainty was developed by Hatziaargyriou et al.^[95], for radial distribution networks. The main limitations are the assumption of a normal distribution for the WPF error, and dependencies are neglected. Morales et al.^[96] presented a PPF that includes uncertainty through the statistical moments (i.e. mean, variance, skewness, and kurtosis) of the distribution and also includes the spatial dependency of uncertainties. The authors proposed an analytical method based on a modified point-estimate method (PEM). The dependent input random variables are transformed into independent variables, using an orthogonal transformation. Furthermore, the authors also described a Monte Carlo method for solving the PPF through simulation, using spatial dependent scenarios. The comparison between the two methods showed that the Monte Carlo method takes about 350 times longer than PEM, and with a 95% confidence level, the solutions provided by both methods are the same. Furthermore, it was shown that the dependency between WPF affects more the active power flow, and an increase in the correlation coefficient results in an increase of the power flow standard deviation.

Usaola^[97] describes an analytical method for PPF based on the cumulant method and the Cornish-Fisher expansion series. A small number of convolution

operations are conducted for multimodal distributions. The method accepts dependent/independent, continuous/discrete random variables. WPF uncertainty is modeled with beta functions conditioned to the level of injected power, and dependent scenarios are generated with a sampling process similar to others in the literature^[31]. The author compared the proposed method with a PEM with independent random variables. The results showed that the PEM attains a good performance (i.e. average error between moments of the power flows) for the independent case up to the second-order moment, whereas the proposed method behaves better in the dependent case.

Bessa et al.^[70] adapted the classical PPF for including WPF uncertainty. A set of forecasted quantiles is converted into a (triangular) fuzzy number. The FPF, in the framework of the ANEMOS, plus project, was operationally demonstrated for the Portuguese SO, and the goal was to detect possible congestions and voltage violations in the market dispatch for the next day. The demonstration showed that in hours where wind power was underforecasted, leading to branch congestion, the deterministic power forecast (PF) was unable to detect congestion, whereas the FPF, depending on the selected cutoff, was capable of detecting possible congestion. Evaluation analysis for the whole demonstration period (six months) showed that deterministic PF has the lowest percentage value of false alarms, but at the same time, has the highest percentage of overlooked congestions. FPF, with a cutoff properly defined by the user, offers a more balanced solution between the percentage of false alarms and the percentage of overlooked congestions.

All reviewed methods were applied only for detecting congestion situations under normal steady-state operation. Some SOs also run power flow calculations with branch contingencies (N-1 regime) as the ENTSO-E Policy 3 suggests^[98]. Moreover, the methods do not define (at least directly) any preventive/corrective action or perform a redispatch for solving the problem.

Vlachogiannis^[99] proposed a constrained PPF that includes uncertainties from both wind power and electric vehicles (EVs). The method uses a learning algorithm based on learning automata systems for determining the values of continuous and discrete control variables. The goal is to determine robust values for the control variables that maintain the risk of constraints' violation below a predefined level. This method has the following limitations: WPF are not included (i.e. wind speed uncertainty is modeled with a Weibull distribution) and spatial and temporal dependencies are neglected.