# Weather and Climate and the Power Sector: Needs, Recent Developments and Challenges

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**Abstract** Weather and climate information is essential to the energy sector. The power sector in particular has been using both observations and forecasts of many meteorological and hydrological parameters for several decades. In the last 10 years, a clear upward trend has been observed in the number, complexity, and value of data provided by National Meteorological and Hydrological Services (NMHSs) or produced by the energy sector itself. Much progress has been made, especially in the medium-term and longer time ranges; the development of reliable probabilistic forecasting systems has allowed many improvements in demand and production forecasts, although there is still a lot to do because of the difficulty in integrating probabilistic weather forecasts in management tools. In addition, the rise of renewable energy (RE) production systems, in particular wind and solar energy, has emphasized new needs for more accurate and reliable short-term forecasts, from real-time to a few days ahead. Rapid fluctuations in wind and solar radiation at local scale certainly raise a serious problem for the management of power grids. Significant and swift improvements in local forecasts, at hourly or even sub-hourly time step, become increasingly important and will be among the drivers for the large-scale development of RE systems. In this paper, we present some important results concerning monthly ensemble forecasts of temperature and river streamflows in France. We then point to the principal needs in weather forecasting associated with the development of RE. We also discuss the importance of collaboration and relationships between providers and users of weather, water, and climate information.

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**Fig. 1** Aerial view of Migouélou dam and lake, © EDF, Gilles De Fayet

## 1 Introduction: The Power Sector is Increasingly Weather Dependent

The power sector is constantly evolving and this has, in particular, been the case in the last 15 years in France, because of the liberalization of the energy market. In addition to physical constraints on the systems, financial factors have become ever more important, bringing even greater complexity to an already complex optimization problem.

Most utility operations are influenced by climatic variables: demand of course depends on temperature, either for heating in winter or cooling in summer; RE production depends on the respective source (wind for wind energy, solar radiation for solar energy, precipitation and river discharge for hydropower, etc.) (Fig. 1)

The importance of weather and climate for economic activity has been the subject of many studies (Marteau et al. 2004; Teisberg et al. 2005; Dubus 2007; Lazo 2007; Rogers et al. 2007; Dutton 2010; Frei 2010, etc.). French energy companies gave figures explicitly on the climatic impact on their activity for the first time in 2010, in their corporate results communication. Electricité De France (EDF), the French leading power company, in particular, evaluated the impact of

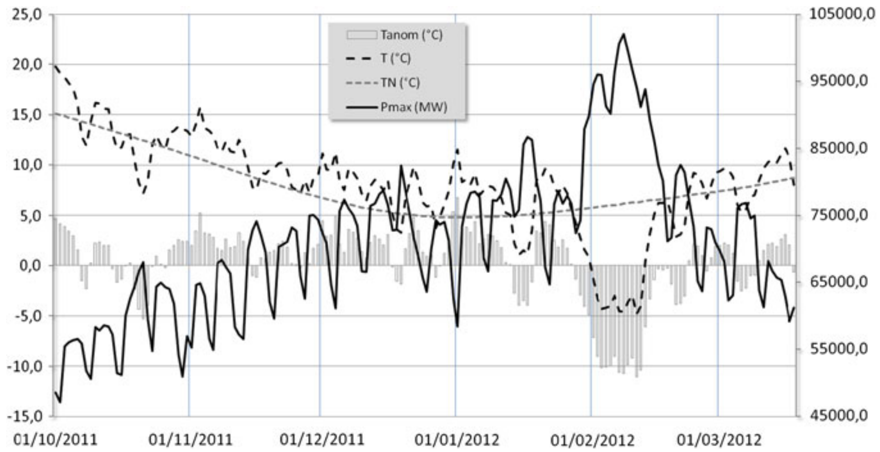


**Fig. 2** Temperature and peak demand in France. Data from Météo-France and RTE (www.rte-france.com): normal temperature (*grey dotted line*), daily temperature (*black dotted line*), temperature anomaly (*bars*), and daily maximum demand (*solid black line*)

weather on the variation in sales and EBITDA[1] (EDF 2011). In 2010, more power was sold, in particular due to cold conditions in winter, and this resulted as a positive impact on both indicators (+€337 million on sales and +€215 million on EBITDA, respectively). Both demand and production in fact depend on weather.

Power demand depends foremost on air temperature, as shown in Fig. 2 which represents, for October 2011 to March 2012, the time evolution of the average temperature over France and of power demand (together with the climate normal and the anomaly with respect to this normal). There is a clear correlation between both variables: when temperature decreases, power demand increases and vice versa. This relationship is commonly defined as the "demand gradient". In France, the winter gradient is 2,300 MW/ °C[2]at around 7:00 PM (the time of peak demand in winter).This means that for an extra anomaly of $-1$ °C (or respectively +1 °C), the demand (and hence, the production required to meet it) increases (respectively decreases) by 2,300 MW, which corresponds to twice the electricity consumption of a large city such as Marseille ( $\sim$ 850,000 inhabitants). The value of this gradient depends on both the time of day and the day of the year. In summer, the maximum value is 500 MW/ °C and is reached at around 1:00 PM.

Clearly, power generation also depends on climate variables. Temperature and river flow determine the cooling capacities of (standard and nuclear) thermal power plants which are located along rivers. Summer heat waves and/or low river

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[1] Earnings Before Interest, Taxes, Depreciation, and Amortization.

[2] The power of a production unit is expressed in megawatts (MW). A nuclear plant has a production capacity of 900–1,600 MW, depending on the technology; the production capacity of a typical windmill is around 1–5 MW.

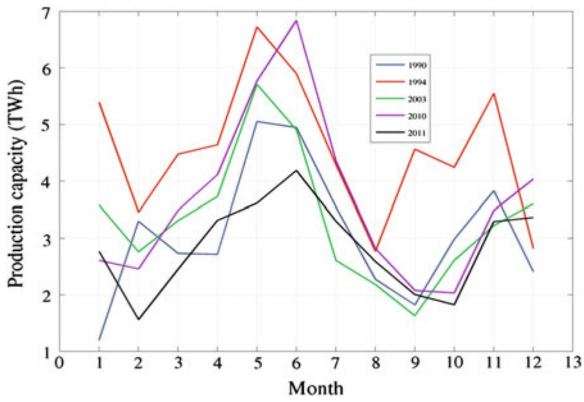


**Fig. 3** From EDF's Financial communication, 2011/02/15. Monthly evolution of hydropower generation potential (TWh), for five different years

water levels, as in 2003, can reduce cooling capacity and thus entail a reduction in production capacity (Dubus and Parey 2009).

The influence of weather parameters is also crucial for RE sources (hydro, wind, and solar). Figure 3 shows the hydropower generation potential for four different years. In addition to a strong seasonal cycle, the production capacity is also marked by a strong interannual variability: in the last 25 years, the difference between highest and lowest annual generation potential was 23 TWh, for a theoretical maximum generation of 44.4 TWh.[3] In 1994, for instance, the autumn was characterized by many perturbations affecting most watersheds, and then strong precipitations that explain the high level of production capacity for this particular year (redline on Fig. 3).

In order to meet both the major challenges facing the power sector (IEA 2011) and political objectives, it is necessary to vastly develop wind and solar power production over the next 30 years. Due to their fluctuating nature, however, wind and solar energy cannot be scheduled in the same way as conventional power plants. This can lead to security problems for the networks and hence to power disruption for customers. Improving the quality of production forecasts is therefore crucial, to enable the development of solar and wind energy suited to the challenges of climate, energy demand and fossil fuel prices in the decades ahead (see also the chapters by George and Hindsberger, Love et al., Renne, Gryning and Haupt in this book).

Demand and production forecasts are thus crucial to the management of power systems, at all timescales. The new market organization over the last 15 years has even emphasized the need for longer term forecasts, in order to optimize the use of the different production means, in particular hydropower reservoirs. This paper is organized as follows: parts 2 and 3 respectively present some recent results from monthly forecasts of temperature and river streamflows in France and show their

[3] 1 TWh (Terawatt. hours) = $10^{12}$ W-h, is a measure of energy, the product of power capacity and the time during which it runs (maximum 8,760 h per year).

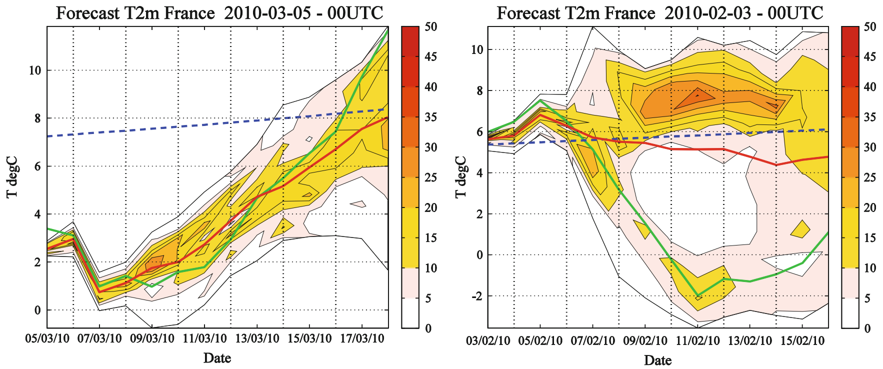


**Fig. 4** 14-day probabilistic forecasts of temperature over France, from ECMWF VarEPS system

improvement in quality, with respect to current reference forecasts. Part 4 discusses some important challenges in the coming years, to improve the use of probabilistic forecasts and the quality of short-term forecasts for RE. The conclusion summarizes the results and gives some important points about collaboration and partnerships between providers and users of weather and climate information.

## 2 Probabilistic Temperature Forecasts of a Few Days to One Month

As seen above, power demand in France depends on air temperature, the winter peak time gradient being on average 2,300 MW/ °C, and around 500 MW/ °C in summer. Temperature forecasts are therefore crucial to the supply/demand balance optimization problem. Deterministic forecasts from Météo-France and the European Center for Medium-range Weather Forecasts (ECMWF) are used routinely for short-term forecasts (Dubus 2010). For more than 10 years now, EDF has been using ECMWF EPS 14-days temperature forecasts and it seemed natural to test the benefits of using longer lead-time forecasts. Figure 4 illustrates the advantages of probabilistic versus deterministic forecasts. The plots represent two different forecasts, up to 14 days, of temperature averaged over France. The color corresponds to the density of the 51 runs of the ensemble predicting the corresponding temperature. For March 5th 2010 (left panel), the forecast dispersion is small, indicating a rather predictable situation, and the ensemble mean (red line) is very close to the a posteriori observed temperature (green line; the blue dotted line is the climate normal for that period): the difference between observation and forecast, up to day 9, is less than 1 °C. In this case, using the ensemble mean as a single deterministic forecast seems quite reasonable and would not lead to large errors, at least up to day 10. On the other hand, the forecast made on February 3rd

2010 (right panel) shows a marked bimodal distribution: most of the ensemble members being around the normal (blue dotted line), with a few indicating much lower temperatures (8 °C lower than the climate normal on February 11th). As shown by the observed values (green curve), the ensemble mean in red is, in this case, far from the observation: on the 12th, the error made using this crude deterministic forecast is 7.1 °C, equivalent to some 16,300 MW at demand peak time or 16.5 % of France's total installed capacity. Taking into account the whole probability distribution would therefore lead decision makers to act differently in the management of the system, with an evident reduction in risk. This clearly illustrates the superiority of probabilistic forecasts, even if the information is much more difficult to deal with and to integrate in existing power system management tools (see also the chapters by Mailier and Dutton in this book).

Although monthly weather forecasting was being studied as early as 1980 (Nap et al. 1981), numerical weather predictions with this lead time only improved significantly about 10 years ago. Since the early 2000s, ECMWF has been developing a monthly forecasting system which is now fully integrated in the VarEPS-Monthly system. It consists of a twice-weekly extension to 32 days of the EPS runs, an ensemble of 51 members at the global scale. The horizontal resolution is around 30 km up to day 10 and from then around 50 km up to day 32 (Vitart 2004; Vitart et al. 2008). In 2004/2005, a subjective evaluation of the forecasts was conducted on the basis of the graphical charts displayed on the ECMWF website, involving end users in the system optimization branch of EDF. Positive feedbacks allowed to study more deeply the potential benefits of such forecasts and to make a quantitative evaluation. A rather extensive study was undertaken, of which only the key results are given here. The evaluation was carried out on forecasts from October 2004, date of the operational release of the monthly forecasting system, up to April 2012 (395 forecasts). The variable of interest is air temperature, averaged over France (the figure is a weighted average of 26 stations in France, with the different weights corresponding to the proportion of total energy demand allocated to the 26 areas). Deterministic and probabilistic scores were calculated and compared to those of 2 reference forecasts: (1) from a historical dataset of 120 years of observed daily data, taken as a reference climatology (this 120-member ensemble always gives the same forecast for a given period) and (2) from a ~15,000-year time series dataset, obtained with a statistical model, which has the same statistical characteristics as the 120-year dataset.[4] These references will henceforth be called REF1 and REF2.

Classical deterministic and probabilistic scores and skill scores (Jolliffe and Stephenson 2011[5]) have been calculated: bias, MAE, RMSE, ACC, rank diagrams, ROC scores, Brier Scores, and reliability diagrams. For the probabilistic scores,

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[4] This 15,000-scenario dataset was established to deal with probability distribution tails (e.g., 1 % quantile), which cannot be estimated accurately with only 120 years of data.

[5] See also the web site maintained by Beth Ebert at http://www.cawcr.gov.au/projects/verification.

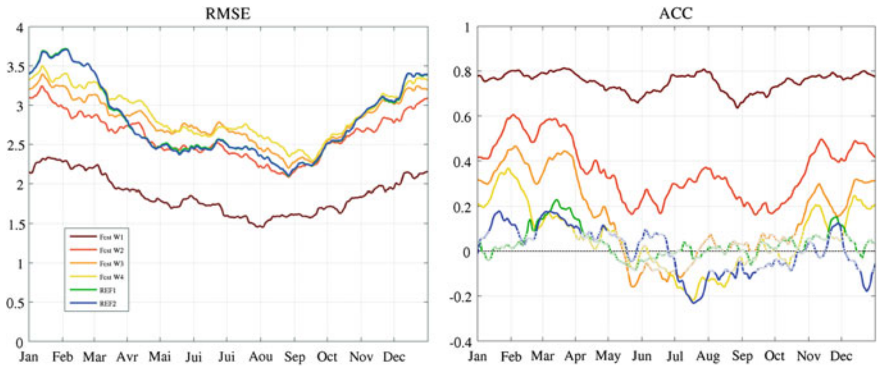



**Fig. 5** RMSE (*left*) and ACC (*right*) of monthly temperature forecasts over France. Weeks 1–4 of the forecasts are in *brown*, *red*, *orange,* and *yellow*, respectively. *Green* and *blue lines* are reference forecasts (see text for details)

different events were considered (Temperature anomaly <−4 °C, <−2 °C, <0 °C, >+2 °C, and >+4 °C; Temperature anomaly <20 % percentile of the climatological distribution and >80 % percentile of the climatological distribution). The verification of each set of forecasts is made against a posteriori observation of temperature, weight-averaged over the 26 reference stations according to the aforementioned procedure.

Figure 5 shows the yearly evolution of two deterministic scores (Root Mean Squared Error and Anomaly Correlation Coefficient) for weeks 1–4 of the forecasts, together with those of the forecasts REF1 and REF2. Monthly forecasts display better scores up to week 2 than REF1 and REF2, throughout the year. The scores continue to be better in weeks 3 and 4 during winter (Dec–Jan–Feb). The Mean Error (not shown here) is of the same order of magnitude for the forecasts and REFs, with a yearly average value approaching 0. Evidently, these forecasts should, due to their nature, be evaluated instead in terms of probabilistic scores, which is presented below.

Only ROC skill scores for temperature forecasts falling below the 20th percentile or above the 80th percentile of the observed distribution are shown here. Figure 6 shows the time evolution of these scores depending on lead time (1–32 days), averaged over all forecasts.

The ROC skill scores (ROCSS) are always positive for both events, hence the forecasts are better than the climatology throughout the period. When compared to forecasts REF1 and REF2, the monthly system is better up to day 20 for both events and for the other thresholds considered (not shown here), although, the higher the amplitude of the anomaly considered (either positive or negative), the better the monthly forecasts.

Figure 7 shows the evolution of the same ROCSS throughout the year, for each week of the forecast. The plots show, first, that there is strong variability, denoted by the high-frequency oscillations, even if the scores were calculated using a

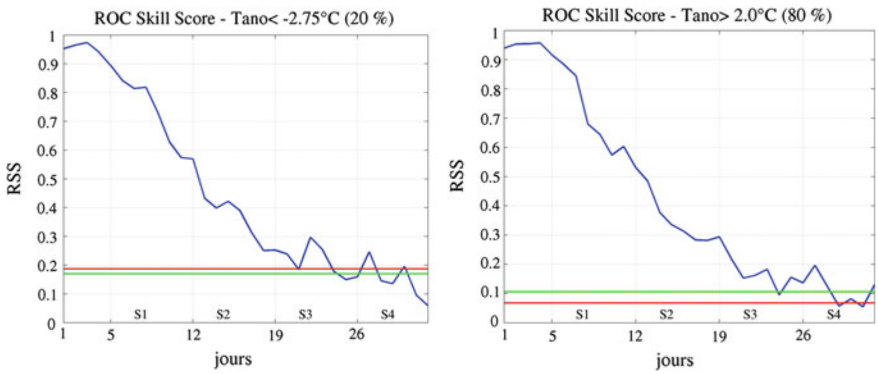



**Fig. 6** ROC skill scores of monthly temperature forecasts over France (*blue line*), for the events: temperature anomaly within the <20 % (>80 %) percentile of the observations. The *red* and *green lines* are the ROCSS of the two reference datasets

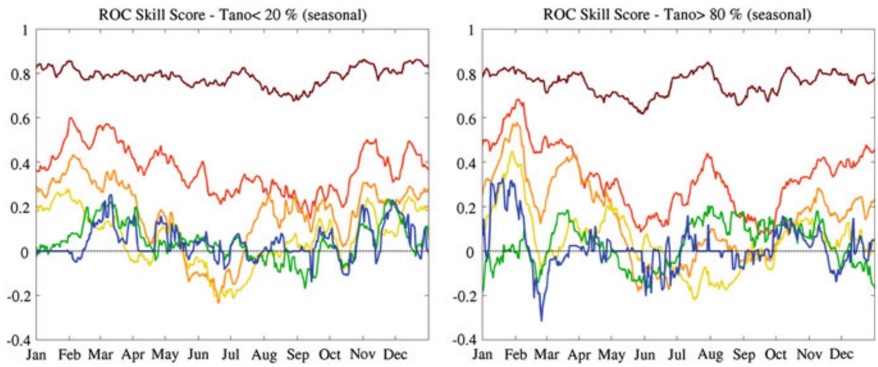



**Fig. 7** ROC skill scores for each individual week and REF1 and REF2 forecasts (same *colors* as Fig. 4 and events as Fig. 5)

smoothing procedure. Monthly forecasts are better than the reference forecasts for weeks 1 and 2, throughout the year and for both events. Secondly, the skill of the forecasts varies through the year, with a maximum ROCSS during winter months (from November to March). In weeks 3 and 4 the conclusions must be moderated, but there is accuracy up to week 3 and even week 4 in December, January, and February, as well as in summer. This is, however, less evident in the intermediate seasons (spring and fall). With the exceptions of June, July, and August for week 4 and June–July for week 3, the ROCSS of the monthly forecasts is always positive and, for the majority of the time, higher than those of the reference forecasts.

The different plots and computed scores all confirm that monthly forecasts provide better information, at least up to week 3 in winter and week 2 (corresponding to days 11–18, that is to say 4 days more than the EPS) over most of the year.

The recent implementation of a second run of the system on Mondays has reinforced the value of these forecasts, which have now been used in operations for more than 3 years. The limiting factor to their use, at present, lies in the lack of integration between the forecasts and the existing tools: the forecasts are not used formally within the operational tools, but instead used as extra information which aids managers in taking their decisions on the management of the power system. A quantitative estimation of the economic benefit of such forecasts is rather difficult to produce, because they are not yet explicitly taken into account in optimization models. However, it is clear that these forecasts can be very useful to decision makers, in particular to anticipate cold spells in winter and heat waves in summer. Certain limitations have been identified and ways to progress will be discussed in Part 4 of this chapter.

## 3 Improvement in Monthly River Flow Forecasts

Hydropower represents 20.6 % of EDF's installed capacity in France, EDF being ranked number 5 in Europe for total installed renewable capacity, at 25 GW in late 2010 (EDF 2012). Hydropower production is very important in the French power system, as it provides a relatively partitionable energy stock, due to the presence of high capacity reservoirs. It therefore provides very attractive flexibility during peaks in demand. The difficulty, however, is that it is essential to manage the storage capacities and therefore to accurately forecast the annual water cycle inflow. At a given time, managers of the system are faced with making the optimal choice between using the water to produce energy in response to a peak in demand, or choosing alternative solutions as e.g. buying energy on the European market and keeping the water available in the reservoirs, should some forecasts show that the water will have a greater value in the days/weeks/months ahead. The problem is not only a question of financial optimization, but perhaps more importantly a physical problem, because rivers have to be managed in coordination with other users (agriculture, tourism, etc.)

Operational forecasts of river flow and water stocks are therefore crucial for the managers of the system. At present, they are generated everyday for the next 7 days, using deterministic and probabilistic forecasts from Météo-France and ECMWF, through an analog method (Zorita and von Storch 1999; Obled et al. 2002; Paquet 2004; Andréassian et al. 2006). Following from the studies made on temperature and reported in part 2, it was decided to evaluate the usefulness of ECMWF monthly forecasts for river flows. These were generated using the same analog method. For each of the 32 days and 50 members of a forecast, the method uses the geopotential fields forecasts at 700 and 1,000 hPa (Z700 and Z1000 respectively) over North Atlantic/Europe and search for analogs in the NCEP reanalysis. Fifty analog dates are kept for each member, so that it produces 2,500 analog weather patterns to the current forecast. The assumption, then, is to consider that for a given large-scale circulation pattern, the local precipitation and temperature at the given site will be the same. Then, referring to EDF's

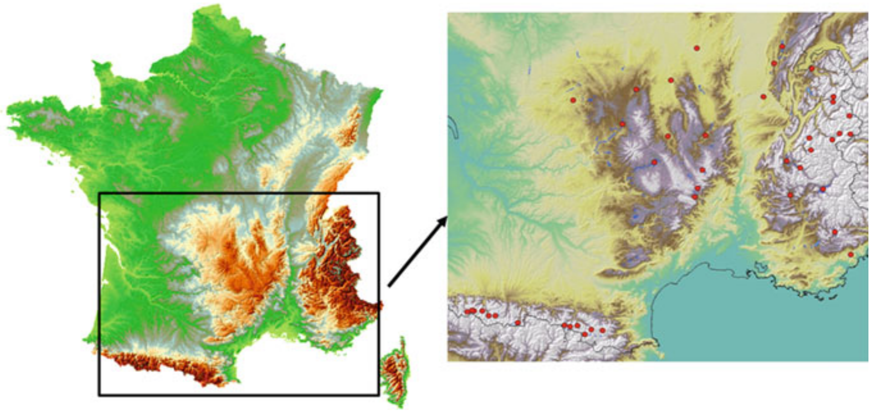
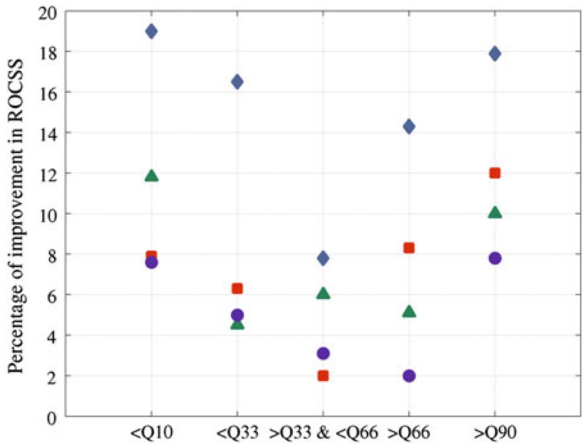


**Fig. 8** Locations of the 43 basins considered for the monthly forecasts of precipitation and stream flows

**Fig. 9** Improvement in precipitation forecast ROCSS for analog versus ECMWF raw forecasts




high-quality precipitation and temperature database from 1953 to 2010, one obtains 2,500 precipitation and temperature forecasts for each time step and each station point considered. The study presented here focused on 43 basins, presented in Fig. 8, and forecasts from October 2004 to April 2010 (291 forecast dates).

A preliminary comparison of direct ECMWF model precipitation forecasts and analog forecasts showed that the analog method improves the local forecasts of precipitation on average over all basins, and over the course of the year. Similar results are observed for 2 m temperature (not shown here). Figure 9 shows the relative gain in ROC skill score taking analog forecasts of precipitation, with respect to the nearest ECMWF grid point forecast, for different events, averaged over each week (1–4) of the 291 forecast start dates. The improvement varies between 2 % for the central tercile in week 4 and about 18–20 % for week 1 and

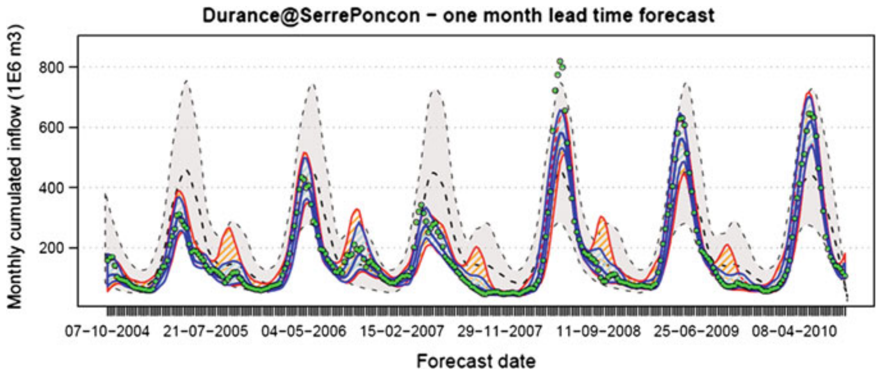



**Fig. 10** Monthly cumulated inflow forecasts for CLIM (*grey*), REF (*orange*) and ANA (*blue*) methods, for the river Durance at Serre-Ponçon. Observed values are in *green dots*

for more extreme events (in the lowest 10 % and highest 90 % of the climatological distribution). Naturally, some local and seasonal discrepancies exist, but the improvements with the analog method are obvious.

The precipitation and temperature forecasts thus obtained are then used in the MORDOR hydrological model (Paquet 2004), to forecast river flows. The model is initialized with observed conditions (water stocks, observed inflows, snow stocks, etc.); the acquaintance with these initial conditions allows the model to make rather good forecasts in mountainous areas in spring, where flow is determined by the melting of the winter snow stock when temperature begins to rise. Of course, the quality of the model is not as good in plains and during the other seasons, because the flow is then less determined by initial conditions, but rather by direct precipitation. During the integration, the hydrological model requires temperature and precipitation forecasts. The current method, for lead times longer than 7 days, consists in using historical time series (1953–2010) in an ensemble climatological approach. It will henceforth be referred to as REF. The alternative method, tested here, is to use the monthly forecasts obtained using the analog method with ECMWF forecasts (referred to as ANA below). A third method can be used, which consists simply in using the streamflow climatology as a forecast (this CLIM is obtained from the 1953–2010 streamflow database).

Figure 10 shows forecasts of the monthly cumulated streamflow obtained with the three methods (CLIM, REF, and ANA) described above, and the observed values (in green) for the river Durance at Serre-Ponçon (French Alps), for the 291 start dates. This plot is a typical one, and summarizes the overall results: first, both REF and ANA methods give better results than the CLIM method, because they are based on the hydrological model, which takes advantage of the acquaintance with initial conditions and the physics of the water cycle. Considering only these two versions of the MORDOR model, monthly forecasts coupled with the analog method allow a better simulation of the inflows: in particular, they provide a narrower dispersion of the forecasts with respect to the observed time series (REF method). This dispersion is nonetheless sometimes too narrow and there are some outliers, but these generally correspond to extremely high inflows due to specific floods, which are very difficult to forecast more than a few days in advance. In the autumn of 2008, for example, the observed inflows were outside of the climatological distribution. There are some examples in which, even if ANA does not forecast high enough inflows, larger values are given than with the REF method. Overall, the most noteworthy point is that the ANA method was much more accurate during the last five autumns, which were characterized by very low water levels: the REF method considers the last 58 years of temperature and precipitation, whereas the ANA method only incorporates the most similar examples with respect to the current large-scale atmospheric pattern, thus excluding not relevant situations from the past.

This study shows, therefore, that even if the raw precipitation forecasts from ECMWF are not very accurate beyond days 10–15, post-processing, via an analog method applied to geopotential fields, can significantly increase the skill of precipitation forecasts and subsequently of water level forecasts. Another important consideration is that better results are obtained when forecasting monthly cumulated inflows, rather than daily time series, in accordance with the general result that long lead-time forecasts have better scores when one looks at integrated measures (Troccoli 2010).

The method used here has already been extensively tested in its 7-day operational configuration, with different predictors, distance criteria (to define analogs), and other key parameters. Although further refinements could be possible, it already gives positive results and has now been released operational. In addition to the better management of hydropower on a monthly timescale, the forecasts can also be used to schedule maintenance operations on dams and production units. An economic assessment of the benefits of such a revised model is planned, even if a difficult exercise.

## 4 Some Challenging Problems

NWP models have significantly improved in the last 10–15 years, in particular at lead times between 10 days and 1 month. In parallel, many efforts were made to better assess the quality and benefits of weather and climate forecasts in conjunction with the sector's economic needs (Dutton 2010; Lemaître 2010; Buontempo et al. 2010). If National Meteorological and Hydrological Services(NMHSs) are pursuing the development of forecasting systems, their customers play (or should play) an important role in defining the priorities to be addressed, in order for their needs to be answered. The paragraphs that follow emphasize some key considerations for the energy sector.

## 4.1 Further Use of Probabilistic Information

Ensemble forecasting is now routinely processed in several NWP centers and used in many sectors: energy, insurance, tourism, etc. (Dutton, in this book). Associated with increasing computational power, it has allowed the limit of predictability to be pushed beyond the 2 weeks suggested by Lorentz in 1963 (Buontempo et al. 2010), as was demonstrated for example in parts 2 and 3 of this chapter. However, one has to deal with several problems when using ensemble forecasts in operational applications.

First, existing tools are often complex systems, with a long history of development and evolution, as is the case with supply/demand optimization models in the energy sector (Dereu and Grellier 2009; Hechme-Doukopoulos et al. 2010; Charousset-Brignol et al. 2011). The integration of weather ensemble forecasts, for example those from the ECMWF VarEPS-Monthly system, is a difficult task because users' systems were not initially built to use such information. In addition, probabilistic information from ensemble forecasting systems is not simple to understand and manipulate for end users, who often have to deal with much information, from many different sources, in real-time decision-making processes.

A second limitation in the use of ensemble forecasts comes from the restricted number of members (typically, 51 at ECMWF). Although this is considered to be sufficient from a meteorological point of view, probabilistic forecasts are notably used to assess extremes, but calculating for instance the 1 % percentile of temperature distribution from 51 members is not straightforward. Current methods generally make the assumption that the temperature is normally distributed and use the mean and standard deviation of the 51 members to then estimate the necessary quantiles. This method gives accurate results as long as the temperature anomaly is not too significant, but can lead to suboptimal decisions when the deviation from normal is significant or when the forecast distribution is bimodal and hence very different from a Gaussian distribution, as is the case in Fig. 4. An internal study has shown that extreme quantiles of temperature distributions can be better estimated using a kernel density estimation and bootstrap resampling from ECMWF EPS ensembles. Further work and research is therefore needed to improve the estimation of forecast distributions from a finite number of members, in particular for distribution tails. As this will have to deal with extreme forecasts and risk optimization, it is a sensitive point which may bring extra value to probabilistic weather forecasts. In addition, "jumpiness" in successive forecasts is very often equated with "bad" forecasting by end users. As stated in Persson and Riddaway (2011), this is a natural characteristic of NWP models, but ways should be found to avoid conveying it to end users, in order to prevent confusion and misunderstanding. A third important point is linked to the fact that optimization models in the power sector generally need the same type of information, whatever the lead time; in particular, temperature information is used at a 3 h time step, for lead times of 1 day to 1 year. If weather forecasts are used up to days 12–14, historical time series (observations) are used in annual optimization models. In the same vein as the seamless forecasting concept developed in NWP (Vitart 2004; Rodwell and Doblas-Reyes 2006; Buontempo et al. 2010), research is under way to find solutions to achieve consistency between medium-range and annual forecasts. The initial idea, unsurprisingly, is to use medium-term forecasts at the beginning of the annual ones, rather than running independent simulations, but this raises the question of how to combine 14 days of 51 members' forecasts with (e.g.,) 100-year-long daily (observed) time series.

Long-term investment strategy and planning are important for the energy sector, with the scope between 10 and 50–60 years ahead. For the longest ranges, climate projections are used. For instance, EDF uses IPCC and CMIP scenarios and complex statistical methods to estimate future extreme temperatures in France and in the UK, in the context of climate change (Parey et al. 2007). Projections are also very important to aid decision-making processes for the next 10–30 years. Renewable energies investment or the adaptation/reinforcement of current facilities and networks require information about the probable climate for the next couple of decades. Decadal predictions for the next 10 years have been used by the UK Met Office to help the energy sector in the UK (Buontempo et al. 2010). Météo-France has developed a method which consists in extrapolating observed trends of the last 30 years to the next decade and then creating a new climatology, centered on the extrapolated mean with the past variability. The homoscedasticity assumption seems fair for extrapolation one decade ahead, but it would need deeper investigation for longer term projections. This method has the advantage of not using decadal climate predictions, which are not yet mature and about which many questions still remain. However, this emerging field of research seems promising and many efforts are currently under way to develop climate services applicable to economic activity, such as the EU FP7 EUPORIAS[6] project for instance.

## 4.2 Local Short-Term Forecasts for Renewables: Wind and Solar PV Power

Although the global use of energy is critical to contemporary human society, the power involved is quite small compared to that in the Earth's environment (Dutton 2010). However, extracting this "natural potential" energy is far from trivial due to its unequal distribution over the Earth, technical challenges, and the characteristics of the different sources. The projected growth of renewables in the decades ahead (IEA 2011) will, moreover, make energy systems increasingly dependent on weather and climate, which calls for a rapid improvement in production forecasting. In particular, the most mature technologies, wind and solar

[6] "European Provision of Regional Impact Assessment on a Seasonal-to-decadal timescale", www.euporias.eu.

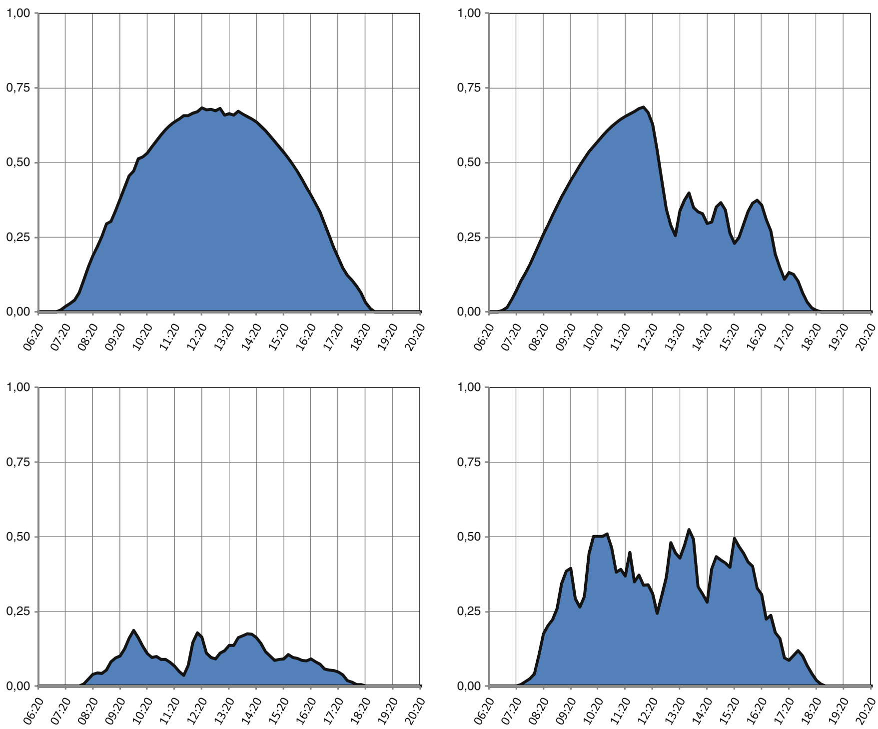



**Fig. 11** Typical daily profiles of PV power production at a site on the island of Réunion (10 mins' data)

energy, are largely dependent on weather conditions. Therefore, research and development is essential to assist energy companies in developing these production means, by improving the reliability of integrating these variable resources and improving economic feasibility (Mahoney et al. 2012). Due to the characteristics of wind and solar radiation, the problem is complex and multi-faceted: both parameters vary quickly in time and space with non-linear impacts on the corresponding power generation.[7] Figure 11, for example, shows 4 typical daily profiles of photovoltaic power production at a single site on the Réunion Island (Indian Ocean). For reviews on wind and solar energy forecasting, one can refer to Lei et al. (2009), Lorenz et al. (2009), Heinemann et al. (2006), and the chapters by George and Hindsberger, Renné, Lorenz, Gryning, Haupt and Coppin in this book.

With the correct weather information, it is generally possible to make rather good power generation forecasts, even though the weather/power relationship is non-linear. Figure 12 shows 1 year of daily photovoltaic (PV) power production at one site on the Réunion island, estimated with two different statistical models

[7] Wind power, for instance, varies with the cube of wind speed.

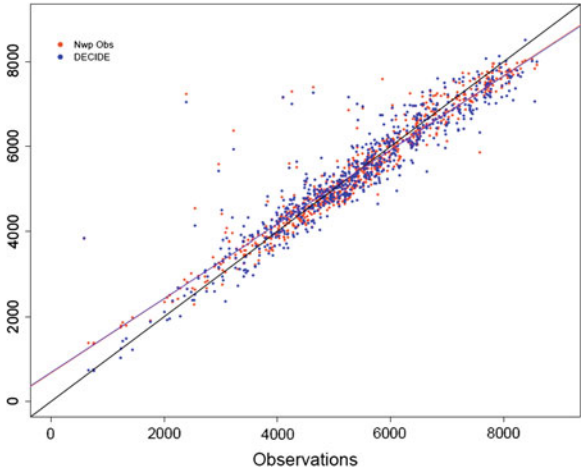



**Fig. 12** Observation (*x*-axis) versus forecasts (*y*-axis) of PV power at one site on the Réunion island. *Red dots* multi-linear regression model; *blue dots* Multivariate Adaptive Regression Splines model. Both models are forced with observed solar radiation data from the nearest weather station

(a multi-linear regression model, and a Multivariate Adaptive Regression Splines based model), and with forcing provided by observed solar radiation from the nearest Météo-France station. Although neither model is perfect, the power production can be modeled with good accuracy as long as the input weather variable is "good." However, when switching from observations to forecasts from NWP, the results are different and model errors grow very markedly. Over the Réunion island, an internal study showed that RMSE can reach 50 % of the average power production at day +1. When considering production at a number of sites dispersed over a large area (a country for instance), the spread allows a significant reduction in the errors, by a factor of ~3 for example over France or Germany, in comparison with a single site. However, in small areas like islands, this averaging effect does not exist; hence local forecasts suffer, in particular, from the lack of resolution in NWP models. Model deficiencies and weather characteristics combine to make the forecasting problem very difficult. Evidently, predictions for locations such as the Réunion island, which are characterized by a very sharp orography and complex convective systems, are even more difficult to make.

However, recent studies showed that significant improvements are possible and involve the integration of multiple technologies. Mahoney et al. (2012) in particular (see also the chapter by Haupt in this book) have developed a complex system which takes advantage of the respective prediction capacities of its different components across the different forecast horizons. Such a system is not commonly used by energy companies at present, because it requires substantial computational resources and many sources of information (about both weather and power production) which are not universally available.

Very short-term prediction is also of great importance, because grid operators need to know, in real-time, how the whole power system will behave in the coming minutes to hours: if some production from a site is to decrease (or increase), the system manager has to adjust other production means, in order to ensure the equilibrium of the system. If the manager does not do so, there are risks to the stability of the grid and a subsequent risk of black-out. For these very short lead times, NWP is useless because models run, in general, from every 6 h (for global models) to every hour (for high-resolution limited area models). For this reason, other forecasting methods are generally used, based on real-time weather observations, both in situ measurements and satellite data and images (Gauchet et al. 2012; Lorenz et al. 2012) on the one hand and recent power production on the other. The latter type of data, in particular, seems promising because it only requires the real-time management of a utility operation's own data. Gomez Berdugo et al. (2012) showed that using only past production measurements allows forecasts up to 3 h with better accuracy than, for example, persistence. This type of method appears particularly interesting when collaboration between neighboring sites is used in the model, which requires centralized or distributed communication architecture. Of course, combining production data and weather data should further increase forecast skill, and further efforts are needed to develop such methods.

Studies (e.g., Mahoney et al. 2012) have shown that improvements in power production forecasting would provide significant financial benefits which would facilitate the faster development of renewables. In order to accommodate a deeper penetration of RE sources into power networks, many challenges still have to be addressed: first, it is essential that weather forecasting centers should provide better forecasts of wind speed at wind turbine height, and of solar radiation. "Better," in this case, means of higher resolution, both in time and space. Naturally, these forecasts should be delivered in a timely manner, so that the lead time of the forecasts is sufficient for them to be taken into account by system management operators.[8] A particularly important point is the prediction of ramps (very rapid fluctuations in power production due to snap changes in wind or solar radiation), which can have serious consequences for grid stability or even cause physical damage in the case of wind turbines. In addition to improving wind and solar radiation forecasts, RE development requires high-quality observations in the dimensioning phase of the projects, in order to evaluate the potential resources. The development of offshore wind energy, in particular, demands offshore wind observations at 100 m height, or, even better, vertical profiles from the surface to 200 m. These are only some examples, and there is no doubt that new data and forecast variables will become essential to the power sector in the future.

[8] For example, a D + 1 forecast at Réunion should be available for the grid operator no later than 16:00 local time on day D, and provide information up to D + 1 at 20:00 local time, in order to be useful. This means that the forecast should be issued at 10:00 UTC up to H + 30, considering a running delivery time of 2 h and the 4-h time lag at Réunion. At the moment, forecasts from Météo-France are issued at 00:00 UTC and 12:00 UTC, for H to H + 30 with the AROME model. In the first case, the forecast does not completely cover D + 1; in the second case, the D + 1 forecast is complete, but arrives too late to be taken into consideration in the planning of the operators.

## 5 Conclusion: Importance of Collaboration Between Users and Providers

The energy industry is exposed to weather and climate variability in the whole range of its activities. The impacts concern all time and space scales. The sector is one of the most important users of weather and climate information and forecasts, and its rapid evolution constantly creates new needs. Long-range forecasts (seasonal to annual and even decadal) become ever more important to the—physical and financial—optimization of the systems, especially for temperature and precipitation, which drive demand and hydropower production. Notwithstanding this, wind and solar radiation observations and short-term forecasts have also become invaluable, and their quality will certainly be among the drivers for the development of RE in years to come.

Scientific progress on its own is not sufficient to increase the value of weather forecasts. There are, in fact, three ways to increase this value (Lazo 2007; Rogers et al. 2007): by increasing forecast quality, by improving communication between providers and users, or by improving the decision-making processes. Each of these three components may be improved separately, but the whole process is undeniably more efficient if the whole chain is improved. This can only be achieved if a close collaboration is set up between the parties. Although state-of-the-art scientific knowledge may put some limitations to possible developments, it remains that the users' needs should be taken into account upstream, and then considered in an iterative process. Only this kind of collaboration can ensure an improvement of operational decision-making processes.

Further communication, collaboration, and partnerships between NMHSs and energy companies are then essential. These synergies will allow to develop better answers to operational needs, but also to add extra value to services provided by weather agencies. Finally, it will be beneficial to the entire society.

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