Ensemble Streamflow Forecasts for Hydropower Systems

Marie-Amélie Boucher and Maria-Helena Ramos

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Abstract

Hydropower operation and planning requires streamflow forecasts at both short (typically, the first 4–5 days) and long ranges (a few months or a season ahead) over different spatial scales. Operational streamflow forecasting services a variety of decisions, made under conditions of risk and uncertainty, e.g., flood protection, dam safety, system's operation, optimization, and planning of power production. In areas where snow falls in significant quantities during winter, spring freshet poses additional challenges given the uncertainties related to the timing and volume of melt water flowing into hydropower reservoirs. Reservoir levels need to be gradually lowered over the winter to make it possible to store snowmelt water in spring. Reservoirs are thus important regulators of streamflow natural variability. They act as a storage place to water that can be used later to meet periods of higher electricity demands or to sell surplus electricity to the power distribution grid. They also usually are multipurpose, and their operation

M.-A. Boucher (✉)
Département de génie civil, Université de Sherbrooke, Sherbrooke, QC, Canada
e-mail: marie-amelie.boucher@usherbrooke.ca

M.-H. Ramos
IRSTEA, National Research Institute of Science and Technology for Environment and Agriculture, UR HBAN, Antony, France
e-mail: maria-helena.ramos@irstea.fr

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must take into account the different water uses, which can, in some cases, be conflictual. The importance of accurate and reliable streamflow forecasts is therefore unquestionable. The hydropower sector has long recognized that streamflow forecasting is intrinsically uncertain and the use of ensemble forecasts is progressing fast. Key challenges today are related to the integration of state-of-the-art weather services, the implementation of systematic, advanced data assimilation schemes, to the assessment of the links between forecast quality and value, and to the enhancement of risk-based decision-making.

Keywords
Hydropower · Energy · Water management · Users · Decision-making · Data assimilation · Economic value · Reservoir · Storage · Multipurpose · Dams · Streamflow forecast · Human expertise · Forecast quality

1 Introduction

Energy production from falling waters to fulfill human's needs for growth has a long history, dating back hundreds of years to the use of water mills for agriculture. The first hydropower facilities, built at the end of the nineteenth century, began exploiting the kinetic energy of water masses flowing through rivers for electricity production (Kumar et al. 2011). In order to better manage the natural variability of river flows in time and be able to store water, dams and reservoirs were built in several river basins around the world. The management of hydropower production is then facilitated, but efforts must still be put into the collection of data and the development of modeling tools for the quantification of river flows. Modeling involves not only the forecasting of future inflows but also the integration of real-time data to asses current conditions of areas upstream of power plants and the analysis of historic time series of streamflow data to set up the model and quantify the long-term availability of local water resources. Hydropower operation also requires market price assessment and forecasts for future energy demand, which is also linked to atmospheric conditions and variability, as is the case of river flows.

Forecasting for hydropower production involves the prediction of several weather and hydrologic variables over a wide range of space and time scales. In space, for instance, one may consider the regional joint production of energy coming from hydropower plants installed at different types of facilities, from run-of-the-river hydroelectricity to production from rivers regulated by small to large dams. In time, as shown in Fig. 1, the needs of the hydropower sector for accurate and reliable forecasts span from forecasts up to 2–3 days ahead for flood protection of the population living downstream the facilities and for the security of installations (e.g., Akabari et al. 2014), medium-range forecasts up to 7–15 days ahead for the value of the production in the electricity grid (e.g. Tang et al. 2010), and long-term (months ahead) streamflow forecasts for hydropower optimization, planning, and seasonal water resources management, including dealing with environment protection measures and concurrent water uses during drought periods (e.g., Lu et al. 2017;

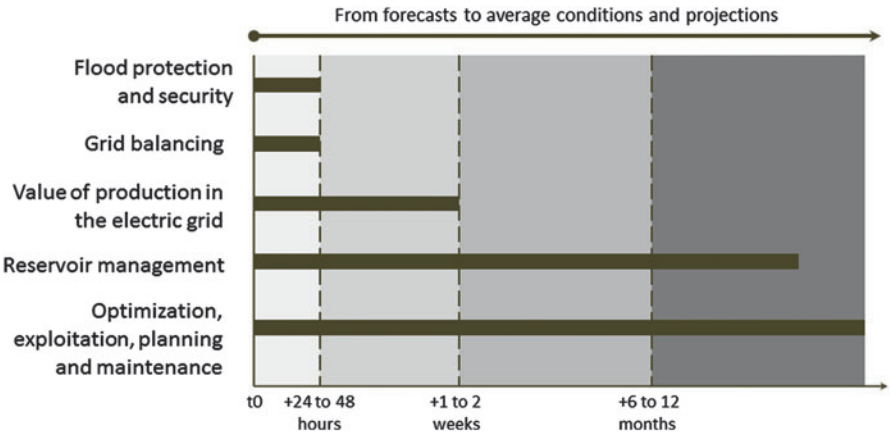

Fig. 1 Time frames in forecasting for hydropower systems

Bazile et al. 2017). The case of multi-year or long lasting droughts represents an especially challenging situation. It results in lower power generation capacities for both run-of-river plants (because of reduced inflows) and storage based plants, as lower reservoir levels translate into lower heads and inefficient water-to-energy conversion (Harto et al. 2011). In addition, drought periods are often associated with an increased demand for energy, attributable to air conditioning (e.g., Vliet et al. 2016). According to Vliet et al. (2016), the most recent recorded droughts throughout the world led to a reduction of 5.2% of hydropower production on average.

Additionally to forecasts, the hydropower industry is also concerned by hydrologic predictions based on future climate conditions and projected trends, as the effects of expected changes in precipitation and temperature may lead to changes in runoff volume, extremes, and seasonality, directly affecting the potential for hydropower generation (Kumar et al. 2011; Schaefli 2015). These issues need to be considered in the long-term planning of hydropower plants and also in the planning of their interaction with other sources of energy (other renewable climate-related energies or nuclear power plants, for instance), notably in views of better managing the storage capacity provided by the reservoirs of regulated rivers (François et al. 2014). Climate change impacts on the hydropower sector can be addressed in contextualized studies (e.g., Boucher and Leconte 2013; Kiani et al. 2013; Hendrickx and Sauquet 2013), which usually include the assessment of regional trends in hydrometeorological variables, the evaluation of future market and economic scenarios, and the implications of expected changes for current management practices and planned adaptation strategies.

Within this broad context, the importance of accurate forecasts and reliable impact assessments is clear. The hydropower sector has long recognized that hydrometeorological forecasting is an essential part of its operations, and the use of ensemble- or scenario-based forecasts is progressing fast (e.g. Boucher et al. 2010; Fan et al. 2016; Séguin et al. 2017). This chapter focuses on the use of short- to long-term forecasts for the hydropower sector. The following subsections provide an overview on the general context of hydropower production, the specificities of streamflow ensemble forecasts for hydropower production, and the main issues behind human expertise, forecast quality, and value in operational forecasting. Key challenges for the industry are presented at the end.

2 The Overall Context of Hydropower Production and Management

Water and energy are intricately linked in different ways. For instance, the extraction of shale natural gas requires large amounts of water; the desalination of sea water to make it drinkable typically requires the use of energy. According to the US Department of Energy (2014), “Historically, interactions between energy and water have been considered on a regional or technology-by-technology basis.” The same report stresses the need for reconnecting energy and water management at the national and even international levels in order to reduce the vulnerability of the worldwide population to climate change and disasters.

Hydropower production remains the activity that establishes the most direct link between energy and water. Water flowing in rivers or stored in reservoirs can be diverted through a turbine to drive a generator that converts the mechanical energy into electricity, which is then distributed to users through transmission lines and connected grids. The dependence of hydropower production on atmospheric and hydrologic variables affects not only energy supply but also users’ demand for electricity. Electricity demand is intrinsically related to weather conditions. It depends mostly on temperature, but also on other atmospheric variables such as humidity or wind, and is subject to seasonal fluctuations and variations across the week and during the day. When associated with storage in reservoirs, hydropower can regulate the natural variability of river flows and help in providing the energy balance between production and consumption, particularly when there is a need to quickly respond to peak load demands and grid stability (Fig. 1).

The flexibility offered by storage-based hydropower is a key feature to help in the stability of electrical systems that highly depend on climate-related (variable) renewable energy sources. Hydropower plants generate the largest share of electricity from renewables. According to Kumar et al. (2011), 12.9% of the world’s primary energy sources were renewable in 2008. In terms of electricity, 19% of the global production in 2008 was from renewable sources, with 16% coming from hydropower. The role of hydropower in increasing renewable energy penetration and ensuring energy security is emphasized with the increasing deployment of intermittent renewable sources such as wind and solar power (François et al. 2016).

The management of hydropower is challenged by the fluctuations in space and time of the weather and hydrologic variables that govern its production. Run-of-the-river hydropower systems are highly dependent on the spatial structure of river networks and the time variability of river flows. Their production is marked by the efficiency of the upstream watersheds in transforming rainfall into runoff and flow in

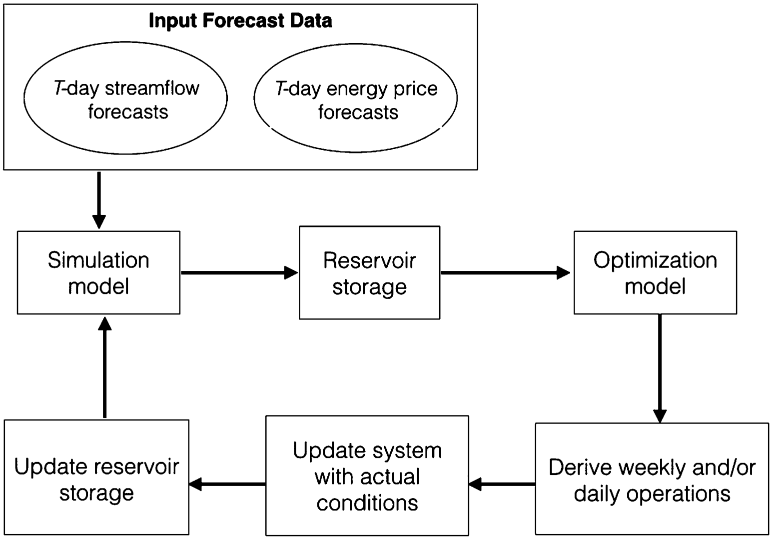

Fig. 2 General framework linking input data and models for the optimal management of hydropower production systems

the channels of the rivers. When associated to large reservoirs, hydropower systems can store water for weeks, months, or even years, smoothing river flow temporal variability. Often these are, however, multifunction systems. The same reservoir has multiple purposes and must also comply with regulations and policies for other uses such as drinking water supply, flood and drought control, navigation, tourism, and environment protection, in addition to energy production (e.g., Tilmant et al. 2008; Björnsen Gurung et al. 2016) . Finally, for some larger catchments, series of reservoirs and hydropower dams are usually installed. The operation of a reservoir upstream may influence the operation of a reservoir downstream. Operation must then be planned in an integrated way. Concertation is key when different owners operate different facilities in the same river catchment. Multi-operator in a multiuser context calls for efficient modeling systems and coordination mechanisms (Anghileri et al. 2013). In these complex situations, hydropower production services will include not only hydrometeorological forecasting systems to provide input to models of reservoir simulation but also reservoir optimization tools to derive optimal and multi-objective operating rules.

The general problem of optimizing hydropower production depends on (1) the forecasts for future streamflows (or reservoir inflows), (2) the type of dam and installed power system (storage capacity, turbine capacity, structural and release constraints), and (3) the forecasts for the energy market prices, which generally reflect variations in electricity demand. Figure 2, adapted from Alemu et al. (2011), illustrates how input forecast data and models are linked in the context of the optimal management of the production of a hydropower plant with storage capacity. In the figure, T represents a forecast horizon expressed in days, which can represent short-, medium-, or long-term forecasts. A typical hydropower producer aims at satisfying the demand for energy at all times during the year, while selling the energy at the highest possible price and managing the facilities as close as possible to optimal, according to future inflow forecasts and management constraints.

Since electricity itself cannot be stored, the reservoir behind a hydropower dam acts as storage place to water that can be used later to meet periods of higher (or peak) electricity demands or to sell surplus electricity to the power distribution grid. Consequently, the optimization of hydropower production searches to define an optimal decision rule between turning turbines on to use the water to produce energy at the present time or turning them off to save water to be used later, at a moment in the future when it might be more valuable. Structural and management constraints play, however, an important role in the optimization. For instance, the storage capacity of a reservoir is limited by its dimensions; inflows from snowmelt and extreme precipitation events need to be accommodated in the reservoir to avoid spilling water due to the occurrence of more water than expected from the forecasts; the occurrence of water levels over the design high water level of the dam or downstream flooding must be avoided for security reasons; downstream flows must be secured for other water uses and to comply with environmental regulations. Figure 3 presents a simplified, schematic view of the management of an inflow forecast to a water reservoir for the production of energy at the best hours of energy prices while respecting reservoir capacity constraints. The management rule defines when to direct the water flow through the turbines to generate electricity and when to store water in the reservoir. In real-time operation, rules and operations are updated on a day-by-day basis, but should always balance short-term and long-term targets (e.g., Lu et al. 2017).

For run-of-the-river hydropower, a small dam or a low head weir is usually created to raise water levels and facilitate water flow diversion to the water intake at the power plant. These ponds, however, do not store enough water for later use as in storage-based hydropower. The management of run-of-the-river hydropower plants is therefore more directly dependant on river flow variability and the forecasts of inflows, with little flexibility to control intermittency in time and manage volumes from extreme events. Flood forecasting is, nevertheless, an important component of such systems, since flood events can damage facilities and threaten onsite workers if rivers overflow their banks. In this context, accurate streamflow forecasts at short lead times (hourly or less) are preferred in order to fine-tune the operations. In the case of multi-objective and complex systems, with some storage capacity, “win-win” situations for hydropower production and flood control can be sought in order to evaluate if flood forecasts can be improved when hydropower production planning is integrated in real-time modeling and operations (e.g., Addor et al. 2011). Additionally, even if the environmental impacts of a small run-of-the-river dam may be lesser than the impact of a large hydropower dam, the physical and biological impacts of

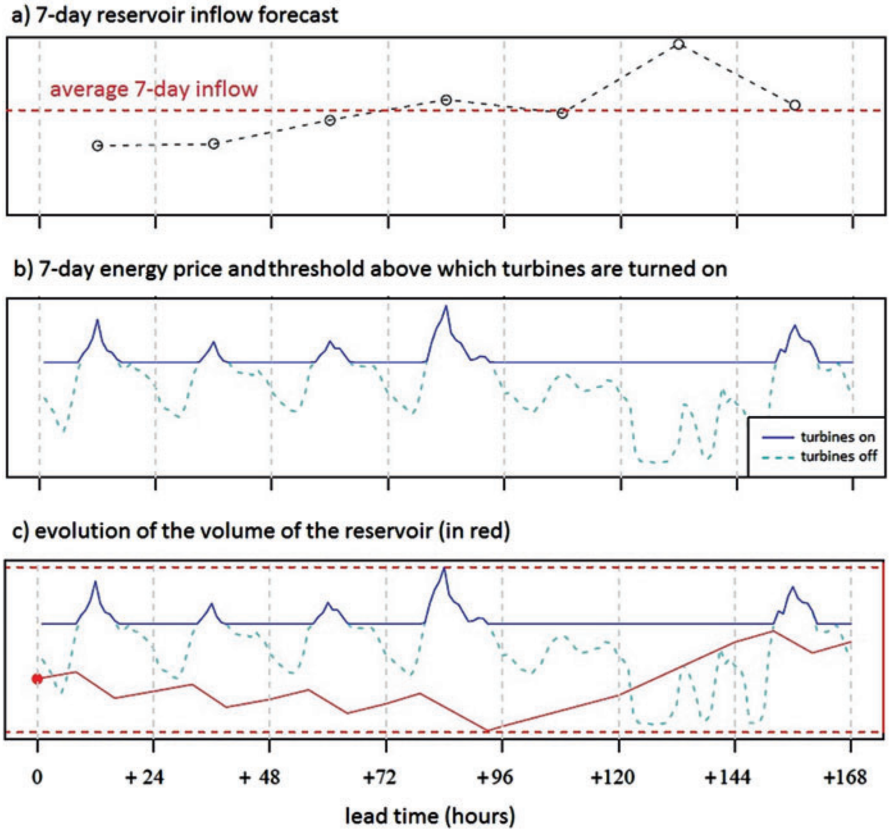

Fig. 3 Simplified scheme of the management of an inflow forecast to a reservoir-based hydropower system: based on a days-ahead inflow forecast (**a**), and on the evolution of energy prices (**b**), optimization techniques define the production of electricity over time (i.e., when turbines should be turned on), considering the best hours for production (i.e., when energy prices are high) (**b**). The volume stored in the reservoir will consequently increase (when turbines are off) or decrease (when turbines are on) (**c**) and should be managed to respect its capacity constraints (maximum and minimum levels, here represented by dashed red lines) and optimize production (i.e., store water when prices are low and release water to the turbines when prices are high). Rules are often updated on a day-by-day basis. This is a simplified scheme, and several other factors are usually considered in hydropower optimization, such as electricity demand, grid security constraints, the existence of other power plants, infrastructure constraints, turbine capacity, or other water use needs

hydropeaking and rapid changes of water levels must also be considered in run-of-the-river hydropower operations. For this, hydrologic data and modeling at both the watershed and the river channel levels are crucial for defining adapted operational strategies and setting up integrated approaches for energy production and ecosystem modeling (Anderson et al. 2015).

3 Ensemble Streamflow Forecasts for Operational Systems

The hydropower sector has long recognized the importance of accurate and reliable streamflow forecasts and simulations as input data to the operation and value of production. They have also acknowledged that forecasts are intrinsically uncertain. Since informed decisions with strong social and economic consequences have to be made, uncertainty needs to be quantified and effectively handled in hydropower operations and planning. It is well known that a single future scenario, no matter how well elaborated it is, is not a good solution to reflect all the possible realities and to base a decision upon. The use of probabilistic- or ensemble-based frameworks in hydrometeorological forecasting, rather than deterministic forecasts, quickly turns out to be an adapted solution to be applied to the modeling challenges of hydropower systems.

In reservoir management and decision-making at seasonal scales, the adoption of probabilistic and ensemble approaches can be dated back to the 1970s. One of the first developers of ensemble approaches for seasonal streamflow forecasting for reservoir operation was the National Weather Service (NWS) California-Nevada River Forecast Center (RFC), which created an operational technique called Ensemble Streamflow Prediction (ESP, which originally stood for Extended Streamflow Prediction; Day 1985; Pica 1997) (An interesting blog post was published in the HEPEX Portal on 26 April 2016, entitled "Tracing the origins of ESP," by Andy Wood, Tom Pagano, and Maury Roos, with special thanks to Mike Anderson, which can be seen at: https://hepex.irstea.fr/tracing-the-origins-of-esp/ (last seen on 16/10/2016).) for applications in water supply management. ESP forecasts are obtained by using historical sequences of observed weather (mostly, temperature and precipitation) as forecast input data to a continuous hydrological model, which is run with current initial conditions up to the time of the forecast. The process results in an ensemble that comprises as many members as there are years available in the observation record. Today, there exist many variants of ESP systems (e.g., Gobena and Gan 2010; Wood et al. 2016) for sub-seasonal to seasonal forecasts, and the availability of seasonal weather forecasts and climate outlooks for a wide range of hydrological applications is also expanding.

By recognizing that climate and meteorological uncertainty should be included more explicitly in their forecasting systems, most hydropower producers have also been investing toward enhancing operational systems with state-of-the-art meteorological forecasts from numerical weather prediction (NWP) models. One example of this approach can be found in the history of developments at the French electric power producer EDF in the past decades. At EDF, the use of probabilities in long-term forecasting is present since the 1950s (Desaint et al. 2009). At this time, forecasts for several (2–3) months ahead were produced using simple statistical methods (linear and nonlinear regressions) and were specifically used for the long-term forecasting of inflows to dam reservoirs. Aware of the intrinsic uncertainties of these forecasts, estimates of future inflows were produced and displayed with the help of confidence intervals. Multi-model GCM's seasonal precipitation forecasts were later explored to improve reservoir management at some months ahead. Garcıa-

Morales and Dubus (2007) reported that such an "ensemble forecast approach provides useful information for EDF catchments, even with quite low skill, and that a deterministic approach, using only the ensemble mean of the forecasts, is not better than a forecast based on climatology." Operational forecasters at EDF also acknowledge that a traditional operational practice of probabilistic-based long-term forecasting has facilitated, although much later, the establishment of the EDF 7-day medium-range streamflow ensemble forecasting system (*personal communication*). In the 1980s–1990s, streamflow forecasts at EDF were based on discharge propagation (hydraulic-based forecasting) in larger river basins and on hydrological (rainfall-runoff) models in smaller catchments. The latter approach used analog-based precipitations as input (i.e., an ensemble of future scenarios created using historic observations of precipitation that were associated with a geopotential field analogous to the forecast one) or deterministic-based numerical weather predictions. In 2008, high-resolution numerical weather predictions and ensemble prediction systems started to be applied in hydrometeorological forecasting (Desaint et al. 2009) (See also the blog post published in the HEPEX Portal on 28 February 2014, entitled "Operational Highlight: use of ensemble hydrometeorological forecasts at EDF (French producer of energy)," contributed by Matthieu Le Lay at: https://hepex.irstea.fr/operational-use-of-ensemble-hydrometeorological-forecasts-at-edf-french-producer-of-energy/ (last seen on 16/10/2016).).

The use of ensemble streamflow forecasts based on medium-range weather ensemble forecasts or analog approaches for short- to medium-range forecasting at daily time steps has progressed fast in the last decade within hydropower systems. For instance, since 2005, the CNR, a historic producer of hydroelectricity on the Rhone (France) river basin in France, runs a precipitation forecasting system based on an adaptation of model outputs through an analog sorting technique operationally in several catchments (Ben Daoud et al. 2009, 2011). Ensemble streamflow forecasting has also been recently implemented by CEMIG, a major group in the electric energy segment in Brazil, based on weather ensembles from multiple sources and large-scale distributed hydrological modeling (Schwanenberg et al. 2015; Fan et al. 2016).

Despite the examples given above, deterministic hydrologic forecasting is still common in short-term operational practice, while ensemble forecasting is more common at longer lead times in reservoir operations for hydropower (e.g., Weber et al. 2006, 2011; Simard 2011; Crobeddu 2014). When only deterministic forecasts are available, these are often post-processed with bias correction and dressing techniques, allowing to take into account uncertainties from modeling or historical information on possible weather scenarios. Figure 4 illustrates a possible framework for a typical hydropower company producing ensemble streamflow forecasts based on deterministic meteorological forecasts and a hydrological model. The data processing step consists in scanning the observed data for inconsistencies and missing data. Manual data assimilation refers to the interaction between the model and operational forecasters, who can manipulate the state variables and the observed data until achieving a satisfying fit between simulated and observed streamflow. The statistical dressing of the deterministic meteorological forecasts can be based on the

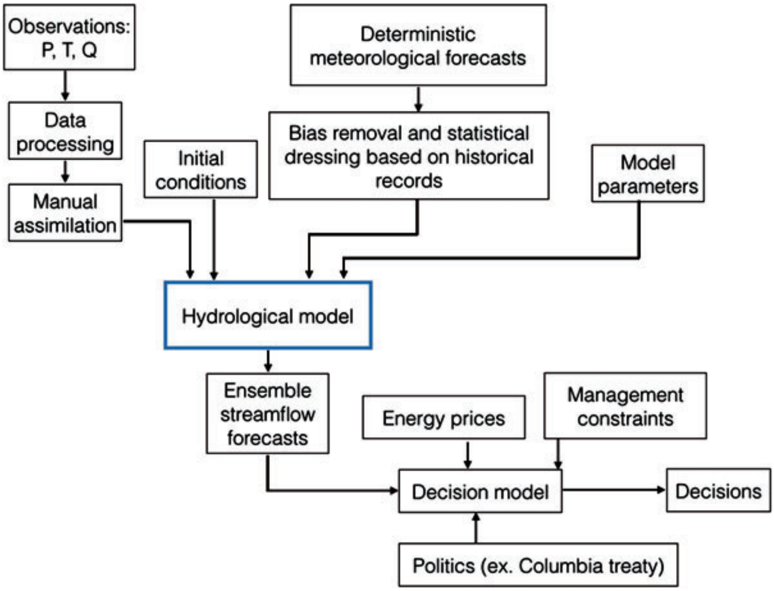

Fig. 4 A typical operational framework for creating streamflow ensembles from deterministic meteorological forecasts in the context of hydropower production

incorporation of an error distribution, estimated based on historical records of observed and forecast archives, to the forecasts. An operational example can be in the context of hydropower production found in Crobeddu (2014). It should be noted that the growing complexity of forecasting systems, with the incorporation of multiple data sources from observational networks and advanced techniques such as ensemble forecasts, prompts to the automation of several operations (which would be infeasible in manual-based systems) and the use of computer-aided decision support systems for an increased efficiency of forecasting centers (Pagano et al. 2016).

4 Human Expertise, Quality, and Value of Forecasts

Although forecasters undoubtedly affect the quality of forecasts through data processing, manual data assimilation and any other form of interaction with the hydrological model, their influence can hardly be dissociated from the type of model used and the type of event being forecast. Having in mind this role of human expertise in improving the forecasts, perceptions and definitions of "what is a good forecast?" are crucial. In his 1993 paper, Allan Murphy defines three types of goodness to consider in the overall assessment of forecasts. *Consistency* reflects the agreement between a forecaster's judgment and the forecast they issue. *Quality* is the agreement between the forecast and the corresponding observation. *Value* relates to the additional benefit to be expected by an end user who would choose to use a specific forecasting system over another. In the context of streamflow forecasting for hydropower systems, it is difficult to isolate one type of goodness, and these three types will be of interest in the evaluation of forecasting systems.

Although forecasters undoubtedly affect the quality of forecasts through data processing, manual data assimilation, and any other form of interaction with the hydrological model, their influence can hardly be dissociated from the type of model used and the type of event being forecast. Given the high level of complexity and sophistication of forecasting systems for hydropower production, forecaster's judgment is considered an important aspect of the forecasting process. Human expertise plays a crucial role in the forecasting centers of hydropower companies. Usually, forecasters can manually adjust the outputs of the hydrological model and correct inadequacies in the meteorological forcing (both observations and forecasts). Where snow processes dominate the hydrological cycle, and an adequate estimation of the snow water equivalent is key to help dam managers to plan the gradual lowering of the reservoir level before spring melt (e.g., Olsson et al. 2016; Bazile et al. 2017), the forecaster can adjust the simulated snow water equivalent by direct insertion of snow water equivalent measured in situ.

For instance, at BC Hydro, a Canadian electric utility in the province of British Columbia, its forecasting system is qualified as a "manual-interactive" system, meaning that the forecasters can adjust both the inputs and the outputs of the hydrological model, as well as its parameters (Weber et al. 2011). At EDF (France), the notion of "subjective probability" in forecasts (Murphy and Daan 1984), based on expertise applied by the forecaster, was introduced early in their practice of operational forecasting (Garçon et al. 2009). Training and case study analyses were considered as efficient means to help forecasters to calibrate their subjective probabilities (or quantiles), with care to avoid issues of overconfidence, i.e., underestimation of total uncertainties (see Ramos et al. 2010 for an example from EDF forecasts and Mannes and Moore 2013 for an interesting explanation of overconfidence, including a quiz). As noted by Garçon et al. (2009), in order to contribute to make human expert forecasts reliable and to facilitate the production of such forecasts in a routine way, it is essential to provide forecasters with probability forecasts that are also objective, i.e., forecasts that are automatically produced by a probabilistic forecasting system. By expressing forecasts through quantiles or scenarios, forecasters are encouraged to give a more formal indication of forecast uncertainty in the forecasts they issue. Training can play an important role, as well as exchange with forecasters form other organizations or hydrological forecasting services. Simulations and games (e.g., Ramos et al. 2013; Crochemore et al. 2016; Arnal et al. 2016), where the forecaster is confronted with typical decision-making problems as well as the forecast of extreme situations that are rarely seen in daily operational forecasting, can also be a good way to open discussions and enhance human expertise.

The quality of a forecast is routinely evaluated against observations by hydropower producers. There exist many definitions of what is a good forecast in the literature. According to Gneiting and Raftery (2007), a good probabilistic forecast maximizes sharpness subject to calibration. Sharpness represents the extent to which the predictive distribution concentrates around a certain value and is a property of the forecasts only. Calibration, in the context of probabilistic forecasting, refers to the statistical consistency between the probabilistic forecasts and the corresponding observations. It is a joint property of the forecasts and the observations. Hydropower forecasting systems will usually care about issuing forecasts that are accurate, sharp, and statistically reliable. The main goals of forecast performance assessment are usually the following:

- Compare the performance of forecasts made by different hydrological models.
- Evaluate the skill of a seasonal forecasting system and its ability to provide better forecasts comparatively to a naïve reference such as climatology or the ESP approach.
- Ensure that all main sources of uncertainty are correctly represented in the forecasting system.
- Help the forecasters to adjust their manual interventions on the raw forecasts or to set up post-processing techniques adapted to their needs and system's configuration.
- Identify the components of the forecasting system that most need improvements or additional human and financial efforts.

Forecast quality assessment is usually carried out through the evaluation of statistical scores (e.g., Brier Score, CRPS, reliability diagram, rank histogram, ensemble spread, MAE, correlation, bias, etc.) over a long archive of pairs of forecast and observation, as well as qualitatively, particularly when dealing with selected events, through the visual inspection of forecast and observed hydrographs. Plots with the ensemble streamflow forecasts traces are usually visualized, together with preselected confidence intervals (e.g., the percentiles 10% and 90%) and the median scenario for forecast communication (Ramos et al. 2010).

Finally, the evaluation of the value of a forecast requires that a decision model (or a reservoir management model) be integrated to the hydrometeorological forecasting system in order to evaluate how valuable (in terms of economic benefits) a good forecasting system can be for the business of a hydropower company. For hydropower systems, the economic value of a forecasting system usually depends on observed losses of water (hence, energy that could be produced and sold in the market) and on the economic values of potential power production. The value of the forecasts can be expressed in different ways: for instance, in terms of revenue brought by good decisions when selling energy in the market or in terms of water loss by spilling (and thus not used to produce energy) as a result of a bad forecast or a non-optimal reservoir management. (For some examples, see the blog posts published in the HEPEX Portal: i) on 31 January 2014, entitled "On the economic value of hydrological ensemble forecasts," contributed by Marie-Amélie Boucher, Maria-Helena Ramos, and Ioanna Zalachori at https://hepex.irstea.fr/economic-value-of-hydrological-ensemble-forecasts/ and ii) on 17 May 2016, entitled "A never-ending struggle – Improving spring melt runoff forecast via snow information," contributed by David Gustafsson at https://hepex.irstea.fr/a-never-ending-struggle-improving-spring-melt-runoff-forecast-via-snow-information/ (last seen on 16/10/2016).). We note that the evaluation of "good" or "bad" decisions is not as straightforward as it appears, even for decision-makers, and measuring the economic consequences of "good" or "bad" forecasts is also a complex exercise for forecasters, managers, and decision-makers. Examples of the assessment of the value of forecasts in the context of hydropower production can be found in the works of Alemu et al. (2011), Boucher et al. (2012), and Anghileri et al. (2016).

5 Key Issues and Future Challenges

In summary, forecasting for hydropower production is a process involving the forecasting of weather and hydrologic variables at a wide range of space and time scales. Forecasting systems are usually integrated with reservoir management models and decision support tools for electricity production. The planning of operations requires short- (several days) to long-term (several months ahead) streamflow forecasts. The use of ensemble streamflow forecasts in the hydropower sector is growing fast, bringing new challenges and opportunities, mainly in terms of integration of state-of-the-art weather services, data assimilation, forecast quality and value assessment, and risk-based decision-making.

- Enhancing the use of meteorological ensemble predictions and weather services

While most hydropower producers recognize the added benefits of assessing meteorological forecast uncertainty through ensemble prediction systems, many still rely on deterministic meteorological forecasts for short-term streamflow forecasts, and on ESP or analog approaches, based on archived observations and strong assumptions of stationarity, for medium- to long-term forecasts. Meteorological centers throughout the world are however increasingly improving their ensemble prediction systems, and many are now routinely also issuing ensemble monthly and seasonal forecasts. The hydropower sector can benefit from including new products in their forecasting systems, specifically in views of setting up seamless forecasting systems that offer consistent forecasts across space and time scales. In existing sophisticated systems, the need for changing traditional practices and validated techniques can however hamper the introduction of new weather products, as it may require running "old" and "new" systems in parallel until comparisons are established and confidence gained. Challenges remain in comparing competing methods to produce better ensemble predictions and defining optimal ways to better explore the information conveyed by state-of-the-art weather services and risk outlooks.

- Operational implementation of systematic data assimilation methods

In most current operational settings of hydrologic forecasting systems, data assimilation is rather rudimentary and performed manually by human forecasters, based on their expertise. Direct insertion is a common practice, which consists in modifying the value of observed meteorological variables (mostly precipitation and temperature) through a trial and error process until the simulated and the observed streamflow values match. These modifications affect the internal state variables of the hydrological model used to issue the forecast. The modification of inputs is justified by the uncertainty related to data acquisition (e.g., measurement errors or insufficient network density). However, there exist many different types of systematic data assimilation schemes that could be used to enhance forecasting systems (Liu et al. 2012), and some of them are especially appropriate for ensemble forecasts. The ensemble Kalman filter (e.g., Clark et al. 2008; Trudel et al. 2014; Thiboult et al. 2016) and the particle filter (e.g., Weerts and El Serafy 2006; Leisenring and Moradkhani 2011; Noh et al. 2014) have both been found useful to improve the accuracy of uncertainty estimation, especially for short lead times, and represent open opportunities for ensemble-based hydropower forecasting.

- Further exploring the link between forecast quality and value

Until now, performance assessment of forecasting systems has mostly focused on forecast quality, which evaluates the correspondence between forecasts and observations. However, hydropower production provides the perfect framework for assessing the performance of forecasts also in terms of their economic value. A gain in forecast quality does not always translate into higher forecast value (e.g., Boucher et al. 2012; Anghileri et al. 2016; Côté and Leconte 2016). However, understanding the link between forecast quality and value is important as it can contribute to channelize investments into specific ameliorations of the forecasting system that will impact also its economic value. Forecast value is highly dependent on the case study configuration and the targeted aims of the application. It is therefore important to promote the development of more case studies that explore the complex relationship between quality and value of forecasts in a variety of applications in the hydropower sector.

- Improving the decision-making process and fostering the participation of end-users in streamlining future activities

As outlined in Maier et al. (2014), although there is a growing body of literature regarding the benefit of optimization methods for decision-making, many water resources managers remain reluctant to apply them in their operational practice. The authors also mention that

> none of the existing approaches offer a generic and holistic solution for effective and efficient uncertainty propagation during the optimization process. Regarding the decision

variables used in optimization-based water resources management approaches; these are almost exclusively modelled as deterministic. However, this often results in rigid, precautionary strategies that may not be sufficiently flexible to adapt to uncertain future changes.

Deterministic forecasts have been progressively replaced by ensemble forecasts as the latter have shown to improve the quality of a forecasting system. There is a call today to also explore the use of ensemble forecasts in optimization models and risk-based decision-making, in order to enhance the value of forecasts for hydropower production.

The challenge here is twofold. Firstly, optimization models need to be more widely used to support risk-based decision-making at all pertinent space and time scales of hydropower production and planning. This involves operationalizing the paradigm shift that has already started about a decade ago and leave the deterministic framework for a probabilistic, uncertain one. Human is by nature uncomfortable with uncertainty (e.g., Kahneman et al. 1982), and, therefore, achieving this paradigm shift is not at all a trivial task. The active involvement of operational forecasters and end-users in the process is essential in this regard (e.g., Wetterhall et al. 2013). Secondly, the choice of a particular optimization model has to be such that the model is able to explicitly handle uncertainty. This uncertainty comes from the future ensemble streamflow forecasts or inflows to reservoirs, but also from market prices of energy and demand forecasts. In addition, future reservoir optimization tools should account more explicitly for the multipurpose vocation of many hydropower dams (e.g., Tilmant et al. 2008). Today, the water-energy nexus is an opportunity for the hydropower sector to promote a more integrated and cost-effective way to approach water releases and allocation in a cross-sectorial planning and strategic decision-making.

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