PROCESSING WEATHER FORECASTS FOR HYDROLOGICAL ENSEMBLE FORECASTING AND DECISION MAKING IN HYDROPOWER

Seasonal Hydrological Forecasting Workshop
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Facts about Statkraft

- European leader within renewable energy
- Norway's largest and the Nordic region's third largest power producer
- Core business areas within hydropower, wind power, gas power and district heating
- A significant player in the European energy exchanges with cutting-edge expertise in physical and financial energy trading and origination
- 403 power and district heating plants with a total installed capacity more than 18,000 MW, and 29 district heating plants with an installed capacity more than 700 MW.
- Total annual power production of 56 TWh, renewable percentage of 99%
- 71.5% of the installed capacity is in Norway, then Europe outside the Nordics with 16.3%, the Nordics excluding Norway with 8.3% and the rest of the world with 3.9%.
- Delivers more power to Norwegian industry than ever before. About 21 TWh annually
- Develops hydropower in emerging markets outside Europe.
- Significant wind power developer. Has completed Sheringham Shoal offshore wind farm off the coast of the UK together with Statoil. (315 MW)
- The Group's gross sales amounted to NOK 52.2 billion in 2014
- 4200 employees and active in more than 20 countries
- Wholly owned by the Norwegian state
Nordic Operations
Power plants are spread out over a vast region

- 207 power plants with a total capacity of approx. 14 GW
  - 149 hydropower plants in Norway
  - 58 hydropower plants in Sweden
  - 1 gas fired plant in Norway
  - 3 wind farms in Norway
  - 2 wind farms in Sweden

- Model inflow to a total of 950 reservoirs

- 147 HBV models
Agenda

1. Introduction
2. Nordic operational challenges
3. Hydrological forecasting
4. Going forward: Combining weather forecasts
2. NORDIC OPERATIONAL CHALLENGES
Reservoir Management: The basic hydropower challenge

Graph showing inflow and consumption over weeks.
The systems can be rather complicated...

Example: ULLA-FØRRE
To produce or not to produce?
WATeR VALUES DETERMINE THE ‘RESERVATION PRICE’ FOR THE INDIVIDUAL RESERVOIR

Our "supply curve" is based on water values for every reservoir.

Water value = alternative cost of producing one extra MWh from the reservoir.
EMPS: Simulations of the Nordic power market

Analyses and Results

- Water values
- Optimal production plans
- Price forecasts with sample space
HYDROLOGICAL INPUT TO EMPS

Updated water levels for 950 reservoirs

Historical precipitation and temperature

EMPS
Nordic countries

83 scenarios for consumption temperatures and wind, coupled with inflow

83 consistent scenarios for inflow and snow for 950 reservoirs; daily resolution, five years horizon

HBV
a precipitation-runoff model

Calibrated against 1980-2010 data

Snow measurements

Weather forecasts
3. HYDROLOGICAL FORECASTING USING HBV
Current operational set-up for simulation of future inflow (and snow levels) using HBV-models

- **Start-state** estimated using observed precipitation and temperature up until today ($t=0$)
  - Updated with snow measurements
  - Manual updating of observed temperatures if significant deviation between simulated and observed inflow

- **Forecast** horizon simulated using 10-day operational EC forecast
  - Manually corrected by meteorologist

- Scenarios for **long-term** horizon simulated from day 10 using end-state from forecast horizon as start state and 83 historical weather years (1931-2013)
  - Series back-filled to 1931
  - Wind corrected precipitation
  - Climate corrected to 1980-2010 mean
...in addition we can in principle process other weather forecast through HBV...

- ECMonthly:

- ECENS:

- Short-term forecast:

...but this information is often lost in decision making as we are not able to process it further through the optimisation models
4. GOING FORWARD

Missing uncertainty

Combining various forecast sources into one dataset
Goal: Improve forecast by addressing missing uncertainty

- Capture missing uncertainty
  - Weather uncertainty first 10 days

- Improve forecast by combining various weather forecast:
  - EC-Monthly
  - ECENS: captures uncertainty
  - Arome or other short-term forecasts

Question: Can we create 83 weather scenarios from day 0 that are consistent with short- and mid-term forecasted probability distributions and match historical scenarios in the long-term?
Example:
Quantile mapping 83 historical scenarios to EC-ENS with interpolation from day 10 to day 14
Scenario $i$ for day $d$ is given by

$$(1 - w(d))F_d^{-1}(H_d(p_i)) + w(d)p_i$$

where $F_d$ is the forecasted CFD for day $d$, $H_d$ is the historical CFD for day $d$, $p_i$ is the historical precipitation value for day $d$ in scenario $i$ and $w(d)$ is a weight function.

So far implemented for EC-ENS forecast…
Idea: Use this method to combine several forecasts into one dataset

- Quantile Map historical scenarios daily to the following forecasts:
  1. EC-Monthly (long-term)
  2. EC-ENS (mid-term)
  3. AROME (short-term)

- Operational meteorologist determines interpolation periods
**Strengths**

- Easy implementation
- Can be used for a wide range of indices (precipitation, temperature, wind, etc)
- Preserves historical correlations in time and space
- Allows for large flexibility in short-term and mid-term forecasting methodology
- Can be combined with other pre- and post-processing techniques

**Weaknesses**

- Does not utilize forecasted correlation properties
  - For instance the quantiles of the QM scenarios may not match the quantiles of the forecast when aggregated in space or time
- Quality of ensemble weather forecast in mountainous coastal region?
  - Need for bias correction?
THANK YOU
Some other refinement possibilities to current set-up

- Use filtering methods for updating start states in HBV model
  - Replacing manual updating of temperatures
- Improve quality of back-filed historical series?
- Calibration of HBV-models?
  - Which calibration data to use? Remove `bad` periods from calibration data?
- Model start state uncertainty
Next step…?
Model start state uncertainty on future inflow using similar approach?

- Idea:
  - Simulate, for instance 10, alternative start states by updating HBV models with perturbed observed temperatures and precipitation
  - For each alternative start state, run HBV models from current date using the 83 QM scenarios for temperature and precipitation
  - In total, this will result in 10x83 alternative scenarios for inflow and snow
  - If this is too many scenarios for the EMPS model, reduce the number of scenarios to 83 by either sampling from the alternative scenarios or by quantile mapping the original 83 scenarios to the 830 alternative scenarios