

Short course on ensemble streamflow forecasting and reservoir optimization

27th IUGG General Assembly, Montréal, Canada

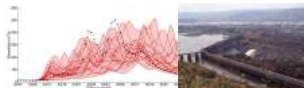
Marie-Amélie Boucher¹ Sara Séguin²

¹Université de Sherbrooke, marie-amelie.boucher@USherbrooke.ca


²Université du Québec à Chicoutimi & GERAD, sara.seguin@uqac.ca

July 9th 2019

Round of introductions...

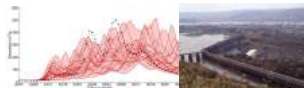


Marie-Amélie Boucher

- ▶ Hydrologist
- ▶ Professor at Université de Sherbrooke (Canada)
- ▶ Research interests: multi-model forecasting, short and long term forecasting, data assimilation, pre and post-processing, assessing the socio-economic value of forecasts.
- ▶  @Queen_MAB_hydro
- ▶ marie-amelie.boucher@usherbrooke.ca



Round of introductions...

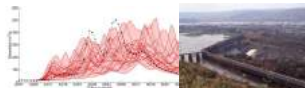


Sara Séguin

- ▶ Operations research specialist
- ▶ Professor at Université du Québec à Chicoutimi (Canada)
- ▶ Research interests: short term hydropower optimization, mathematical formulations (nonlinear, linear, linear integer), unit commitment, stochastic optimization.
- ▶ sara.seguin@uqac.ca



Round of introductions...



- ...And you?



Get Account

Apps

Resources

STUDENT LOGIN

TEACHER LOGIN

Have you gone PRO?

GET PRO

Outline

Ensemble streamflow forecasting

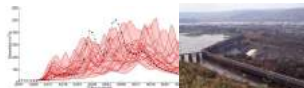
- First, some basics!

- Sources of uncertainty

- Verification

- Data Assimilation

- Pre- and Post-processing



Hydropower

- Basics

- Hydropower optimization

 - Decision making process

 - Uncertainty

 - Reservoir optimization

 - Short-term optimization

References



Ensemble streamflow forecasting



UNIVERSITÉ DE
SHERBROOKE



GERAD

GROUP FOR RESEARCH
IN DECISION ANALYSIS

UQAC

Université du Québec
à Chicoutimi

Some basics: Why Forecasting?



<https://ici.radio-canada.ca/nouvelle/1032244/inondations-degradation-precipitations-pluie-quebec-rivieres-niveau-eau>

<http://ici.radio-canada.ca/nouvelle/516710/richelieu-inondations-monteregie>

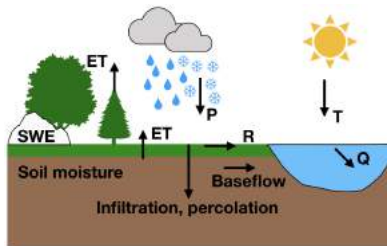


from [5]

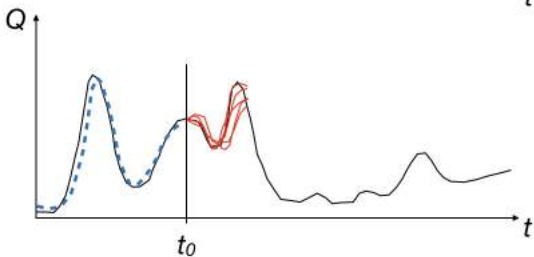
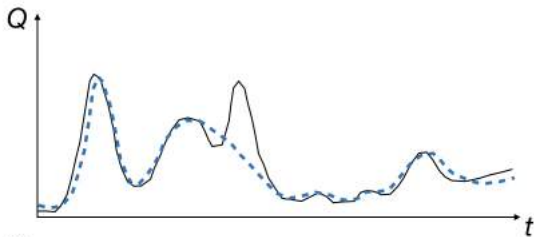
Some basics: Simulation vs forecasting



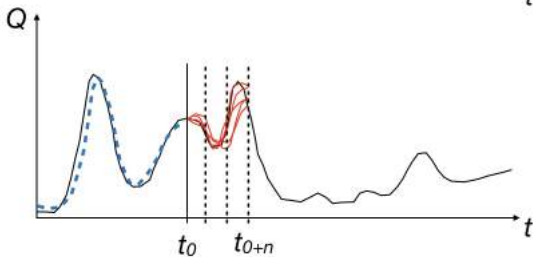
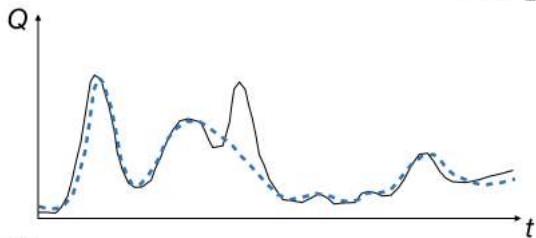
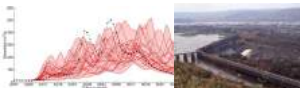
- ▶ A (hydrological) model includes inputs, outputs, fluxes and state variables
- ▶ It also contains equations, with free, initially undetermined parameters



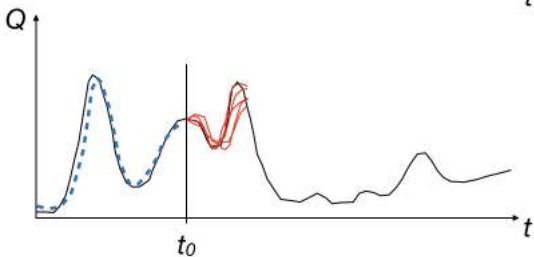
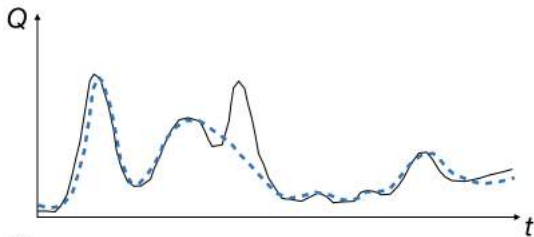
Some basics: Simulation vs forecasting



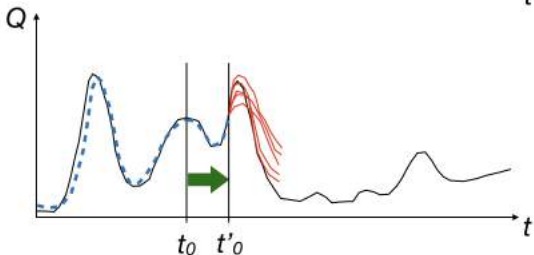
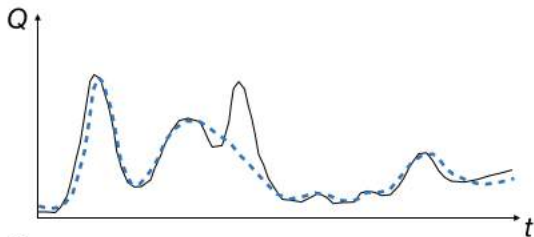
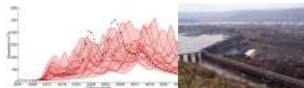
Some basics: Simulation vs forecasting



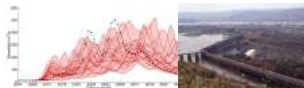
Some basics: Simulation vs forecasting



Some basics: Simulation vs forecasting



Sources of uncertainty



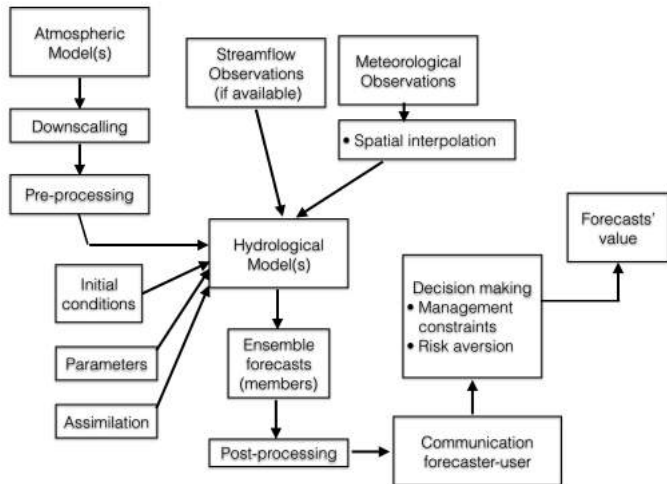
According to you, what are the main sources of uncertainty in hydrological forecasting?



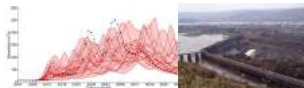
Zoom

Enter Answer Here

Sources of uncertainty



Verification



Zoom

What is a "good" ensemble or probabilistic forecast?

Enter Answer Here

(Source for the figure:

<https://pixabay.com/photos/goodbadoppositechoicechoose-1123013/>)

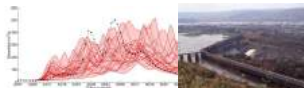


- ▶ Sharpness and reliability

- ▶ **Sharpness:** "concentration of the predictive distributions and is a property of the forecasts only. The more concentrated the predictive distributions are, the sharper the forecasts, and the sharper the better, subject to [reliability]" [13]
- ▶ **Reliability:** "refers to the statistical consistency between the distributional forecasts and the observations and is a joint property of the predictions and the observed values." [13]

The predictive confidence intervals must be in agreement with their definition. E.g. The 95% confidence interval should include, on average, 95% of the observations.

Verification



- ▶ Continuous Ranked Probability Score [19]

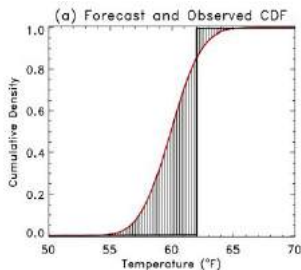
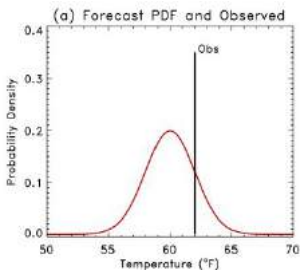
$$CRPS(F, y) = \int_{-\infty}^{\infty} (F(t) - H(x \geq y))^2 dx \quad (1)$$

- ▶ F: Forecast (cumulative distribution function)
- ▶ y: observation
- ▶ x: streamflow values
- ▶ H: Heavyside function
- ▶ For an ensemble of M members:

$$CRPS(x, y) = \frac{1}{M} \sum_{i=1}^M |x_i - y| - \frac{1}{2M^2} \sum_{i=1}^M \sum_{j=1}^M |x_i - x_j| \quad (2)$$

- ▶ This reduces to the Mean Absolute Error (MAE) for deterministic forecasts ($M = 1$)

Verification



https://www.met-learning.eu/pluginfile.php/5277/mod_resource/content/6/www/english/msg/ver_prob_forec/uos3b/uos3b_ko1.htm

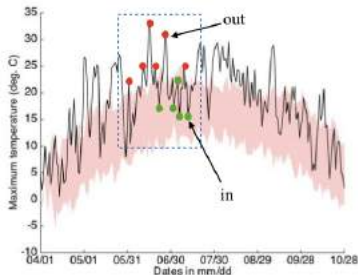
- ▶ Logarithmic (or ignorance) score [14]

$$\text{ign}(f, y) = -\log(f(y)) \quad (3)$$

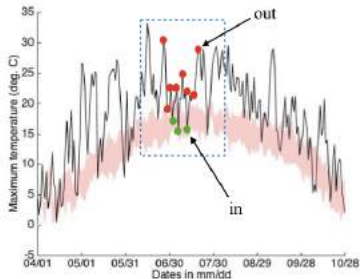
Verification



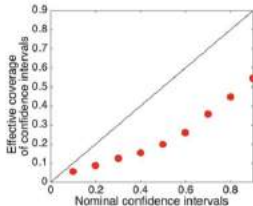
90% confidence interval (nominal)



50% confidence interval (nominal)



- For each level of confidence, verify if the observation is *inside* or *outside* the confidence interval
- Do it for *each time step*, each *forecasting horizon*, etc.



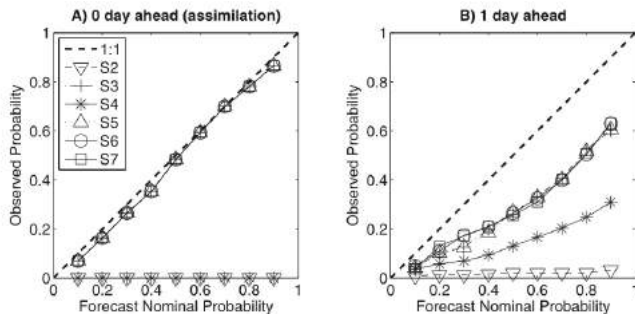
ibac



Verification

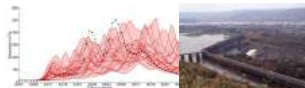


► Reliability diagram [33]

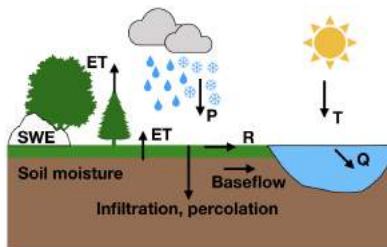


From Ouellet-Proulx S., Chimi-Chiadjeu O., Boucher M.-A., and St-Hilaire A. 2017 :
Assimilation of water temperature and discharge for ensemble water temperature
forecasting *Journal of Hydrology*, 554, 342-359

Data Assimilation



- ▶ A (hydrological) model includes inputs, outputs, fluxes and state variables
- ▶ It also contains equations, with free, initially undetermined parameters

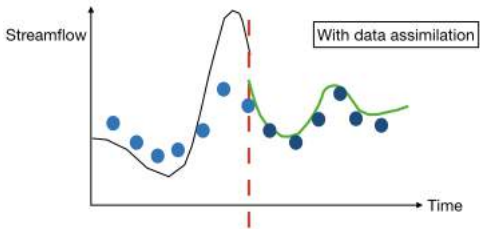
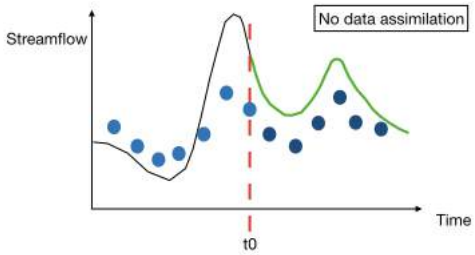




Distinction between calibration, post-processing and DA:

- ▶ Calibration: Obtaining values for the **free parameters** that provide good results **on average**, over a long period.
- ▶ Post-processing: **statistically** correcting the model **output** a posteriori so that it is more in agreement with the observation(s).
- ▶ DA: Updating the **state variables** (and sometimes parameters...) at time t_0 , just before issuing a forecast for the next N days.

Data Assimilation



Data Assimilation

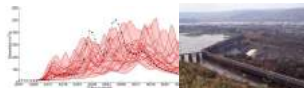


- ▶ Compromise between the model simulation ("background") and the observations
- ▶ Many variants exist!
 - ▶ Direct insertion: the forecaster trusts the observations entirely
 - ▶ Manual data assimilation
 - ▶ Ensemble Kalman filter
 - ▶ Variational DA
 - ▶ Particle filter



Manual, expert-judgement based DA

- ▶ The most widespread method among operational agencies
- ▶ Pros
 - ▶ Very simple to understand and to implement!
- ▶ Cons
 - ▶ Hardly reproducible
 - ▶ Not systematic: highly dependant on individual forecaster's knowledge and experience



Manual, expert-judgement based DA

1. Add noise to the model's input(s) for the last T days before t_0
 - ▶ Additive or multiplicative
 - ▶ There are guidelines / rules of thumb
2. Re-run the model, to compute new state variables
3. Check (visually or using a numeric criteria) that the simulated flow from T to t_0 matches the observed flow better than the **open loop** simulation.
4. Better? Leave it like that, proceed with forecasting
5. Not better? Worst? Try again!



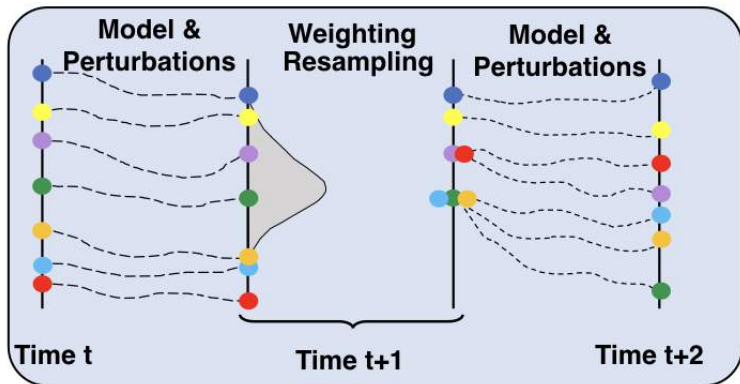
Basic Principles

- ▶ Based on Bayes theorem:

$$p(H|E) = \frac{p(E|H)p(H)}{p(E)} \quad (4)$$

- ▶ H : A hypothesis (here regarding the state of the model)
- ▶ E : Event (here, streamflow observations)

Data Assimilation



(Modified from [29])



UNIVERSITÉ DE
SHERBROOKE



GERAD

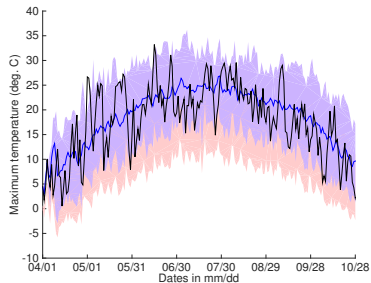
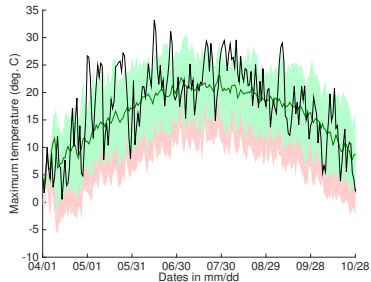
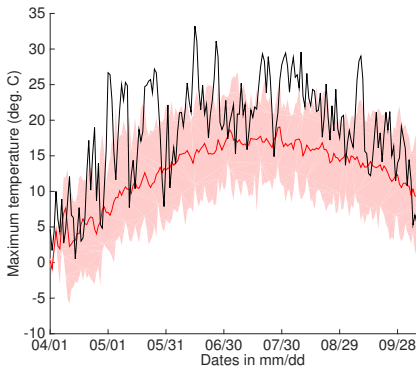
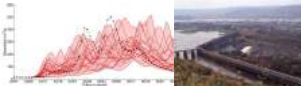
GROUP FOR RESEARCH
IN DECISION ANALYSIS

UQAC

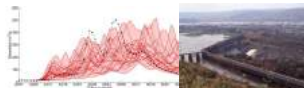
Université du Québec
à Chicoutimi

Pre- and Post-processing

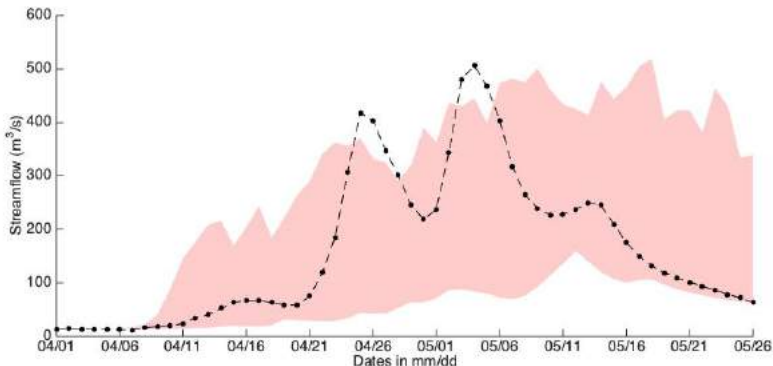
- ▶ Modified from SEAS5 ensemble forecasts over the Kénogami Lake watershed (Quebec, Canada)
- ▶ Initially biased and under dispersed



Pre- and Post-processing



It is important to get the traces right! Problematic example for seasonal hydrological forecasts for Lake K enogami (Canada)



UNIVERSIT  DE
SHERBROOKE



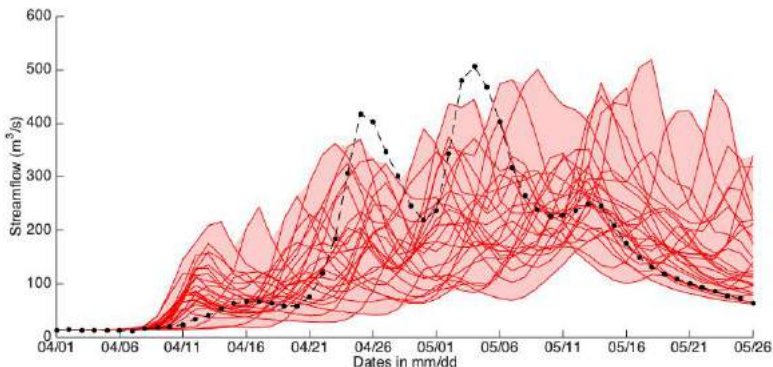
GERAD
GROUP FOR RESEARCH
IN DECISION ANALYSIS

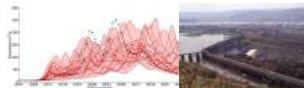
UQAC
Universit  du Qu bec
  Chicoutimi

Pre- and Post-processing



It is important to get the traces right! Problematic example for seasonal hydrological forecasts for Lake K enogami (Canada)

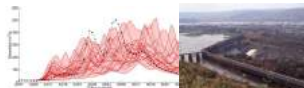




We have discussed:

- ▶ Some definitions: simulation vs forecast, calibration vs data assimilation, etc.
- ▶ Sources of uncertainty
- ▶ Verification: CRPS, logarithmic score, reliability diagram
- ▶ Data Assimilation: basic ideas
- ▶ Pre- and Post-processing: basic ideas





We have not yet discussed:

- ▶ Structural uncertainty
- ▶ Seamless forecasting and how long-term forecasts are different than short-term forecasts
- ▶ Data Assimilation: details of popular methods
- ▶ Pre- and Post-processing: details of popular methods + is it better to pre- or post-process?
- ▶ Forecasts communication and use for flood mitigation
- ▶ ...



Hydropower



UNIVERSITÉ DE
SHERBROOKE



GERAD

GROUP FOR RESEARCH
IN DECISION ANALYSIS

UQAC

Université du Québec
à Chicoutimi

What's next?

Ensemble streamflow forecasting

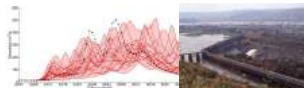
First, some basics!

Sources of uncertainty

Verification

Data Assimilation

Pre- and Post-processing



Hydropower

Basics

Hydropower optimization

Decision making process

Uncertainty

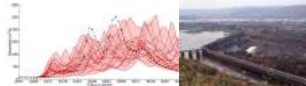
Reservoir optimization

Short-term optimization

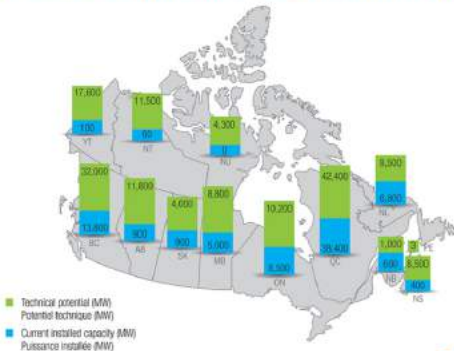
References



Hydropower



CANADIAN HYDRO CAPACITY & POTENTIAL (MW) L'HYDROÉLECTRICITÉ AU CANADA: PUISSANCE INSTALLÉE ET POTENTIEL (MW)



Source: 1) Potential (MW) study conducted for the CMA in 2007. Executive Summary
2) Installed Capacity: Hydroelectricity, 1999-2008 and 1971-1998, revised for 2008 and 2013. Hydroelectricity, 1, 2013
Note: The potential is defined as the technical potential determined by CMA in the CMA in 2007 since the capacity added since 2006 and therefore is more available for future development.



- ▶ In Canada, 63% of the total energy is produced with hydropower

Canadian Hydropower Association, 2019.[4]



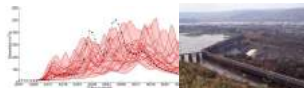
UNIVERSITÉ DE
SHERBROOKE



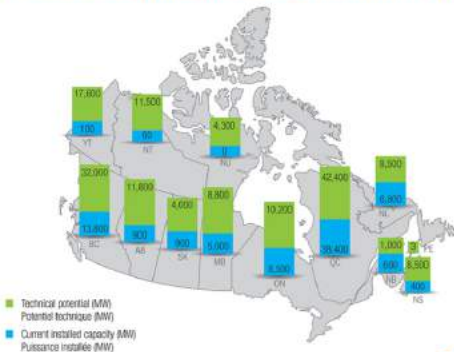
GROUP FOR RESEARCH
IN DECISION ANALYSIS

UQAC
Université du Québec
à Chicoutimi

Hydropower



CANADIAN HYDRO CAPACITY & POTENTIAL (MW) L'HYDROÉLECTRICITÉ AU CANADA: PUISSANCE INSTALLÉE ET POTENTIEL (MW)



Source: "Potential (MW) study conducted for the CMA in 2007" Executive Summary

Current installed capacity: Hydroelectricity, 2008/09 value: 127,400 MW, valued for 2008 and 2013 (hydroelectricity value: 1,200)

Note: The potential is defined as the technical potential determined by CMA in the CMA in 2000, 2007 since the capacity added since 2006 and therefore is more available for future development

- ▶ In Canada, 63% of the total energy is produced with hydropower
- ▶ In the province of Québec, 97% of the energy is produced with hydropower



Canadian Hydropower Association, 2019. [4]



UNIVERSITÉ DE
SHERBROOKE



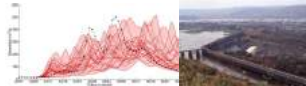
GERAD

GROUP FOR RESEARCH
IN DECISION ANALYSIS

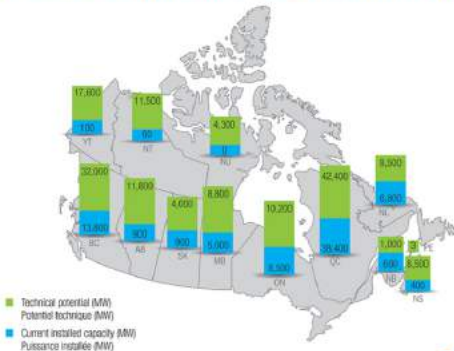
UQAC

Université du Québec
à Chicoutimi

Hydropower



CANADIAN HYDRO CAPACITY & POTENTIAL (MW) L'HYDROÉLECTRICITÉ AU CANADA: PUISSANCE INSTALLÉE ET POTENTIEL (MW)



Source: "Potential HEP study conducted for the CMA in 2007" Executive Summary
 "Installed Capacity: Hydroelectricity, 2008" table 127-9999, accessed 2010 and 2013 via www150.com/energy/9999/9999
 Note: The potential is defined as the technical potential determined by CMA in the CMA in 2000, 2007 since the capacity added since 2006 and therefore is more available for future development.

- ▶ In Canada, 63% of the total energy is produced with hydropower
- ▶ In the province of Québec, 97% of the energy is produced with hydropower
- ▶ Hydropower is a clean and renewable energy



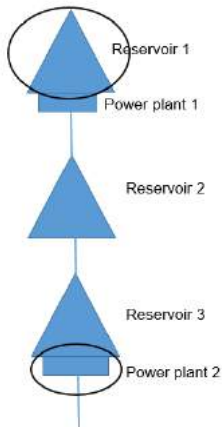
Canadian Hydropower Association, 2019. [4]



Hydropower system



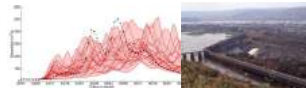
An hydropower system is constituted of multiple power plants:



Each power plant contains one or more turbines



Power plants: two types



Reservoir



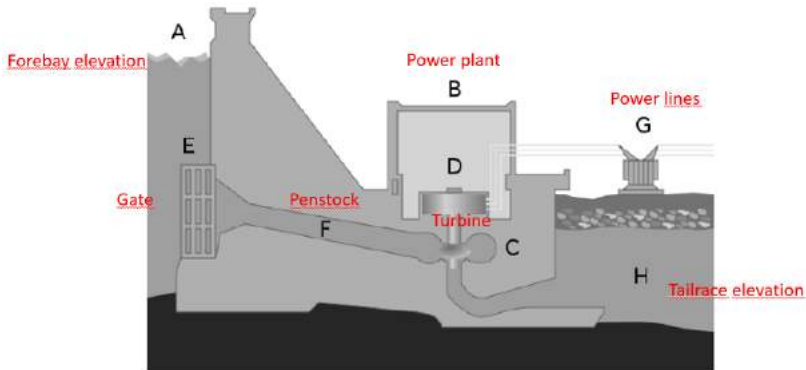
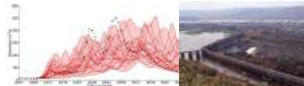
Alaindg, 2007.[30]

Run-of-the-river



Iguanebobo, 2010.[31]

Power plant



Hydrocover plant. Adapted with permission from « Hydroelectric dam » by Torres, 2008. Image under license BYOL and CC-BY-2.5.

Turbine



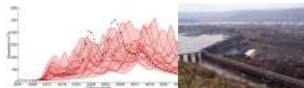
Florival fr, 2010.[32]

Power production



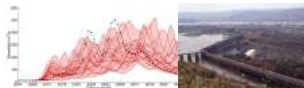
- ▶ Water is brought to the turbine by the penstock.

Power production



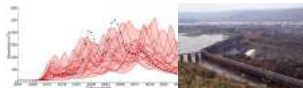
- ▶ Water is brought to the turbine by the penstock.
- ▶ The turbine turns with the force of water and the mechanical energy is transformed in electrical energy with the alternator.

Power production



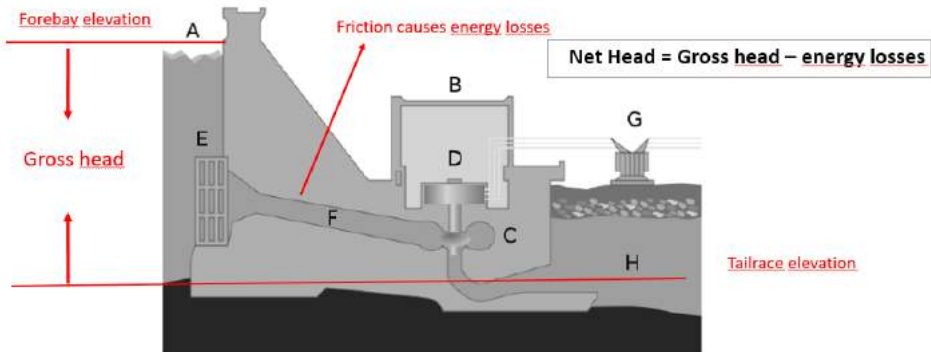
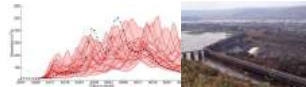
- ▶ Water is brought to the turbine by the penstock.
- ▶ The turbine turns with the force of water and the mechanical energy is transformed in electrical energy with the alternator.
- ▶ The power produced depends on two variables: the water flowing through the turbine and the net water head.

Power production

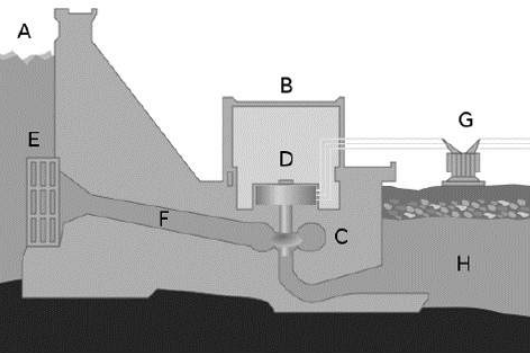
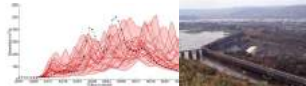


- ▶ Water is brought to the turbine by the penstock.
- ▶ The turbine turns with the force of water and the mechanical energy is transformed in electrical energy with the alternator.
- ▶ The power produced depends on two variables: the water flowing through the turbine and the net water head.
- ▶ For run-of-the-river plants, power produced is usually dependent only on water flow.

Power production

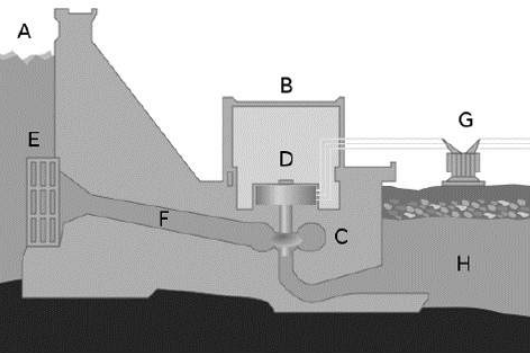


Tailrace elevation



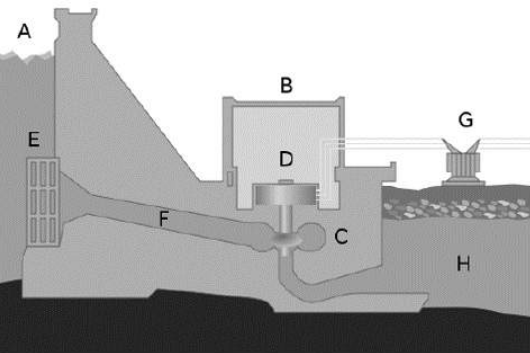
- ▶ The water flow is processed by the turbines.

Tailrace elevation



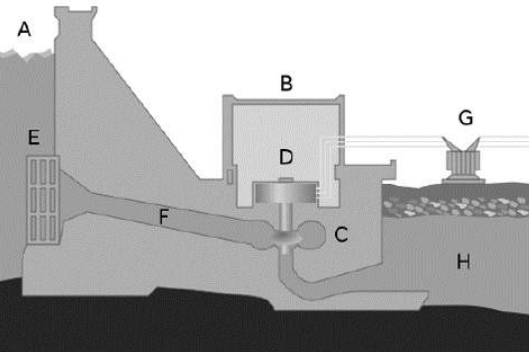
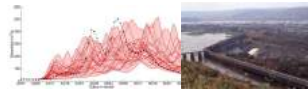
- ▶ The water flow is processed by the turbines.
- ▶ The water then moves to H.

Tailrace elevation



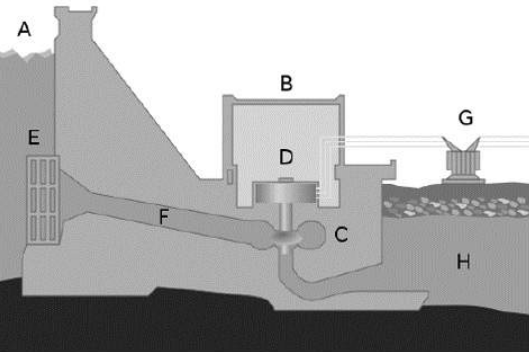
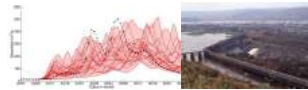
- ▶ The water flow is processed by the turbines.
- ▶ The water then moves to H.
- ▶ The tailrace elevation varies.

Tailrace elevation



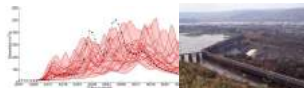
- ▶ The water flow is processed by the turbines.
- ▶ The water then moves to H.
- ▶ The tailrace elevation varies.
- ▶ Which in turn, varies the net water head.

Tailrace elevation



- ▶ The water flow is processed by the turbines.
- ▶ The water then moves to H.
- ▶ The tailrace elevation varies.
- ▶ Which in turn, varies the net water head.
- ▶ The tailrace elevation is a function of the **total** water discharge.

Power production



Power produced by a single turbine is given by:

$$P = ((h_f - h_t(Q_{tot})) - \text{energy losses}) \times \mu(Q) \times Q, \quad (5)$$

where

h_f is the forebay elevation, h_t the tailrace elevation, Q_{tot} the total water discharge, Q the unit water discharge and μ the efficiency.

Hydropower optimization



UNIVERSITÉ DE
SHERBROOKE



GERAD

GROUP FOR RESEARCH
IN DECISION ANALYSIS

UQAC

Université du Québec
à Chicoutimi

Hydropower optimization



The goal of hydropower optimization is to **manage efficiently** the hydropower system.

On an operational basis, daily decisions must be taken:

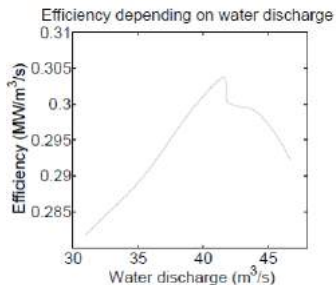
- ▶ The net water head (or volume)
- ▶ The water discharge
- ▶ The turbines working

Other considerations

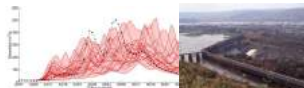


Besides power production itself, other considerations need to be accounted for when making decisions.

► Efficiency



Other considerations

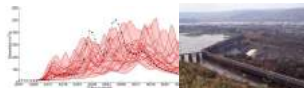


Besides power production itself, other considerations need to be accounted for when making decisions.

- ▶ Turbine startups

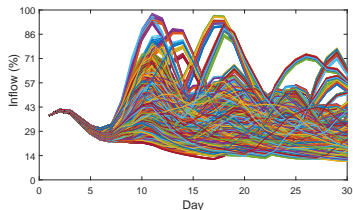


Other considerations

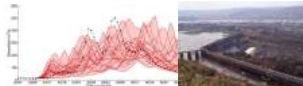


Besides power production itself, other considerations need to be accounted for when making decisions.

► Uncertainty



The decision making process



In practice, medium term and short term optimization models are used.

- ▶ **Medium term or reservoir optimization.** Estimate the quantity of water available for production. Determine reservoir trajectories based on water travel times between plants, reservoir levels, natural inflows uncertainty.
- ▶ **Short term.** Dispatch the water available between the turbines and the plants.

Optimization

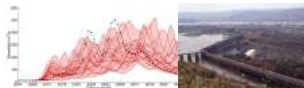


Optimization seeks to minimize a cost function or maximize a profit by finding the optimal value of \mathbf{x} (decision variable):

$$\min c^T x$$

$$\text{s.t. } Ax \leq b,$$
$$x \geq 0.$$

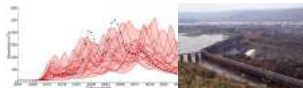
Optimization



Optimization seeks to minimize a cost function or maximize a profit by finding the optimal value of \mathbf{x} (decision variable):

Objective function

$$\begin{aligned} \text{s.t. } Ax &\leq b, \\ x &\geq 0. \end{aligned}$$



Optimization seeks to minimize a cost function or maximize a profit by finding the optimal value of x (decision variable):

Objective function

s.t.

Constraints
Bounds

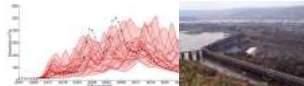
Objective function



Usual objective functions:

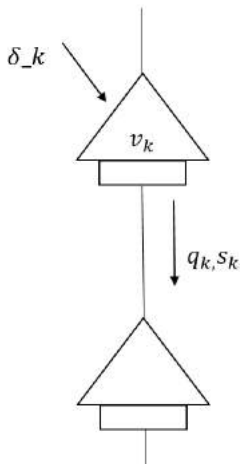
- ▶ Maximize energy production
- ▶ Minimize operation costs
- ▶ Maximize profits
- ▶ Minimize efficiency losses

Constraints and considerations



- ▶ Water conservation

$$v_{k+1} = v_k - q_k - s_k + \delta_k$$

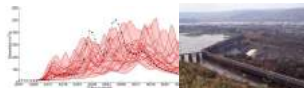


Constraints and considerations



- ▶ Boats, beaches (bounds on water flows, volumes)

Constraints and considerations



- ▶ Boats, beaches (bounds on water flows, volumes)
- ▶ Energy demand

Constraints and considerations



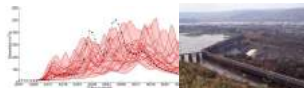
- ▶ Boats, beaches (bounds on water flows, volumes)
- ▶ Energy demand
- ▶ Turbine startups

Constraints and considerations



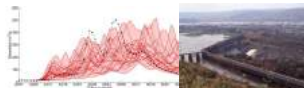
- ▶ Boats, beaches (bounds on water flows, volumes)
- ▶ Energy demand
- ▶ Turbine startups
- ▶ Flooding

Constraints and considerations



- ▶ Boats, beaches (bounds on water flows, volumes)
- ▶ Energy demand
- ▶ Turbine startups
- ▶ Flooding
- ▶ Environmental constraints

Constraints and considerations



- ▶ Boats, beaches (bounds on water flows, volumes)
- ▶ Energy demand
- ▶ Turbine startups
- ▶ Flooding
- ▶ Environmental constraints
- ▶ **Uncertainty**

Uncertainty



UNIVERSITÉ DE
SHERBROOKE



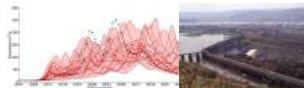
GERAD

GROUP FOR RESEARCH
IN DECISION ANALYSIS

UQAC

Université du Québec
à Chicoutimi

Uncertainty



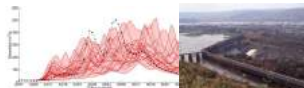
In the context of hydropower, uncertainty arises from:

- Inflows

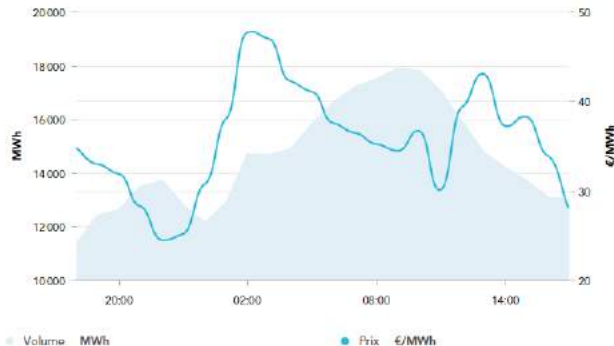


A. Vicente, U.S. Forest Service[28]

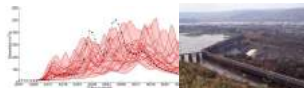
Uncertainty



► Prices



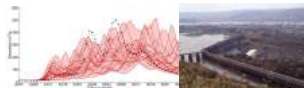
Uncertainty



In the province of Québec, since the electricity market is owned and operated by Hydro-Québec, producers negotiate fixed price contracts.

The only uncertainty that we consider in our models is related to the **inflows**.

Stochastic optimization



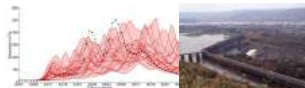
- ▶ Stochastic optimization methods solve problems which contain uncertain parameters at the moment of taking a decision.

Stochastic optimization



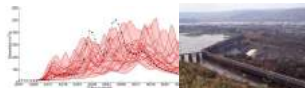
- ▶ Stochastic optimization methods solve problems which contain uncertain parameters at the moment of taking a decision.
- ▶ Reservoir optimization (medium term) and short term optimization use different methods to solve stochastic problems.

Reservoir optimization (medium term)



- ▶ Weekly decisions on yearly horizons

Reservoir optimization (medium term)



- ▶ Weekly decisions on yearly horizons
- ▶ Total water discharge and reservoir volumes

Reservoir optimization (medium term)



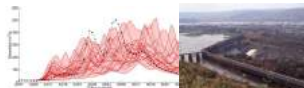
- ▶ Weekly decisions on yearly horizons
- ▶ Total water discharge and reservoir volumes
- ▶ Uncertain inflows

Reservoir optimization (medium term)



- ▶ Weekly decisions on yearly horizons
- ▶ Total water discharge and reservoir volumes
- ▶ Uncertain inflows
- ▶ Turbines are aggregated

Reservoir optimization (medium term)



- ▶ Weekly decisions on yearly horizons
- ▶ Total water discharge and reservoir volumes
- ▶ Uncertain inflows
- ▶ Turbines are aggregated

Commons algorithms:

- ▶ Stochastic dynamic programming (SDP)

Reservoir optimization (medium term)

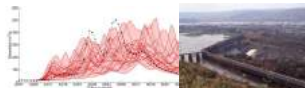


- ▶ Weekly decisions on yearly horizons
- ▶ Total water discharge and reservoir volumes
- ▶ Uncertain inflows
- ▶ Turbines are aggregated

Commons algorithms:

- ▶ Stochastic dynamic programming (SDP)
- ▶ Stochastic dual dynamic programming (SDDP)

Reservoir optimization (medium term)



- ▶ Weekly decisions on yearly horizons
- ▶ Total water discharge and reservoir volumes
- ▶ Uncertain inflows
- ▶ Turbines are aggregated

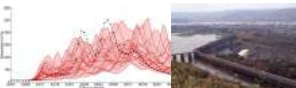
Commons algorithms:

- ▶ Stochastic dynamic programming (SDP)
- ▶ Stochastic dual dynamic programming (SDDP)
- ▶ Sampling stochastic dynamic programming (SSDP)

Dynamic programming (DP)

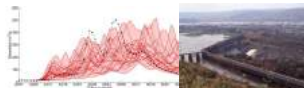


- ▶ Separates a complex problem into sub-problems (stages)
- ▶ Is based on the Bellman optimality principle: *An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision* [1]
- ▶ Stochastic dynamic programming: extension of DP

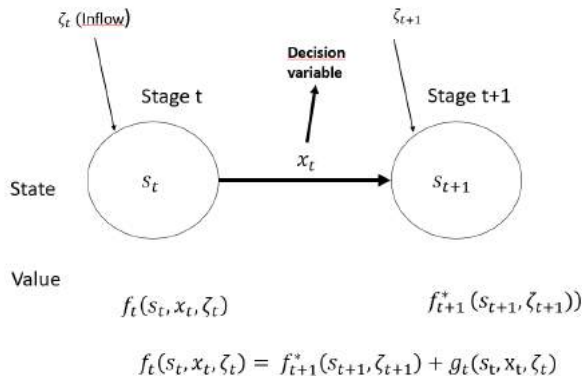


Many discretizations are required:

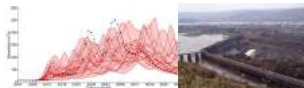
- ▶ Stages: time periods
- ▶ State variables: reservoir storage
- ▶ Decision variables: water discharge
- ▶ Random inflows: Required to calculate the transition probabilities (markov process) between each discrete inflow.



We maximize the expected energy production.



Short-term optimization



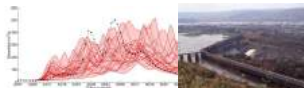
- ▶ Hourly decisions on weekly horizons

Short-term optimization



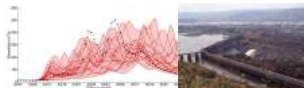
- ▶ Hourly decisions on weekly horizons
- ▶ Result: Water discharges, reservoir volumes and turbines working

Short-term optimization



- ▶ Hourly decisions on weekly horizons
- ▶ Result: Water discharges, reservoir volumes and turbines working
- ▶ Uncertain inflows

Short-term optimization



- ▶ Hourly decisions on weekly horizons
- ▶ Result: Water discharges, reservoir volumes and turbines working
- ▶ Uncertain inflows

Common algorithms:

- ▶ Linear and nonlinear programming

Short-term optimization



- ▶ Hourly decisions on weekly horizons
- ▶ Result: Water discharges, reservoir volumes and turbines working
- ▶ Uncertain inflows

Common algorithms:

- ▶ Linear and nonlinear programming
- ▶ Integer programming

Short-term optimization

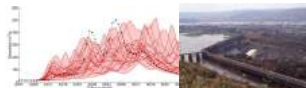


- ▶ Hourly decisions on weekly horizons
- ▶ Result: Water discharges, reservoir volumes and turbines working
- ▶ Uncertain inflows

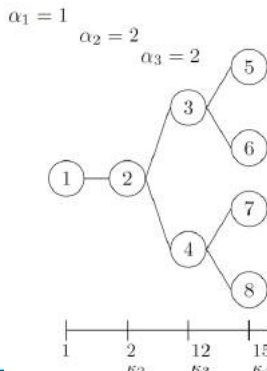
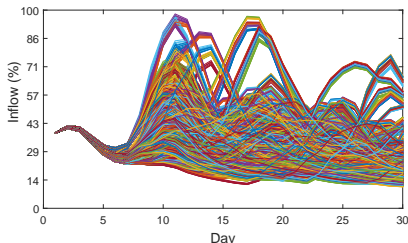
Common algorithms:

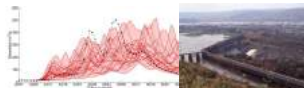
- ▶ Linear and nonlinear programming
- ▶ Integer programming
- ▶ Stochastic programming

Inflows



From the forecasting team, we receive multiple inflow scenarios. Their number is too large for the stochastic program. An approximation, with a scenario tree, is then required.





Example of a short-term stochastic problem:

$$\max_{\mathbf{y}, \mathbf{q}, \mathbf{r}} \sum_{c \in C} \sum_{s=1}^{n_c^s} \chi_{st}^c y_{st}^c \zeta_t + \sum_{c \in C} \sum_{j \in K} \pi_j^c \left(\sum_{i \in N_j} \sum_{s=1}^{n_i^j} \chi_{st}^c y_{st}^c \zeta_t + \sum_{p \in I_j} \Phi_p^c(t, r_p) \right) \quad (12)$$

$$\text{subject to: } \chi_{st}^c \leq \Psi_s^{lc}(q_t^c, r_t^c), \quad \forall c \in C, \quad \forall i \in N, \\ \forall s \in \{1, 2, \dots, n_i^c\}, \quad (13)$$

$$\chi_{st}^c \leq \Psi_s^{hc}(q_t^c, r_t^c), \quad \forall c \in C, \quad \forall i \in N, \\ \forall s \in \{1, 2, \dots, n_i^c\}, \quad (14)$$

$$\delta_t^c = r_{t+1}^c - r_t^c + \gamma W_t^c q_t^c \\ - \sum_{n=1}^{n^c} \gamma W_{tn} q_{tn}^c, \quad \forall i \in N_j, \quad \forall j \in K, \quad \forall c \in C, \quad (15)$$

$$\sum_{s=1}^{n_i^c} y_{st}^c \leq 1, \quad \forall i \in N, \quad \forall c \in C, \quad (16)$$

$$y_{s0}^c = \beta_{s0}^c, \quad \forall s \in \{1, 2, \dots, n_i^c\}, \quad \forall c \in C, \quad \forall i \in N, \quad (17)$$

$$r_{t \min}^c \leq r_t^c \leq r_{t \max}^c, \quad \forall i \in N, \quad \forall c \in C, \quad (18)$$

$$q_{t \min}^c \leq q_t^c \leq q_{t \max}^c, \quad \forall i \in N, \quad \forall c \in C, \quad (19)$$

$$q_t^c \geq 0, \quad \forall i \in N, \quad \forall c \in C, \quad (20)$$

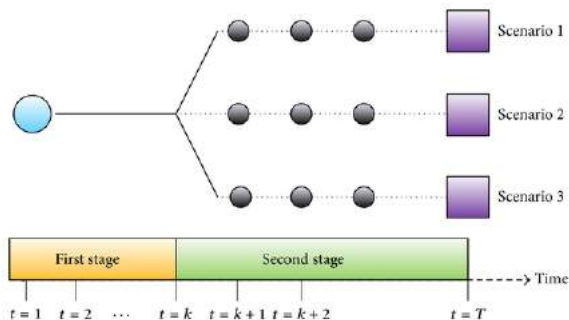
$$r_t^c \geq 0, \quad \forall i \in N, \quad \forall c \in C, \quad (21)$$

$$y_{st}^c \geq 0, \quad \forall s \in \{1, 2, \dots, n_i^c\}, \quad \forall i \in N, \quad \forall c \in C, \quad (22)$$

Stochastic programming



The scenario tree, which is a discrete representation of the distribution of inflows, is then used to solve the deterministic-equivalent of the stochastic program.



Stochastic programming



The model maximizes **first stage decisions (no uncertainty)**, the **expectancy of future production (second stage)** and the **expected value of water remaining in the reservoirs**.

From mid-term

$$\max_{q, v} \chi(v_1, q_1, \delta_1) + \sum_{j \in K} \pi_j \left(\sum_{i \in N_j} \chi(v_i, q_i, \delta_i) \right) + \sum_{t \in K} \pi_t \left(\sum_{p \in E_t} \Phi_p(v_p) \right)$$

$$\text{s.t. } \delta_i = v_{i+1} - v_i + q_i, \quad \forall i \in N_j, \forall j \in K,$$

$$v_{min} \leq v_i \leq v_{max}, \quad \forall i \in N,$$

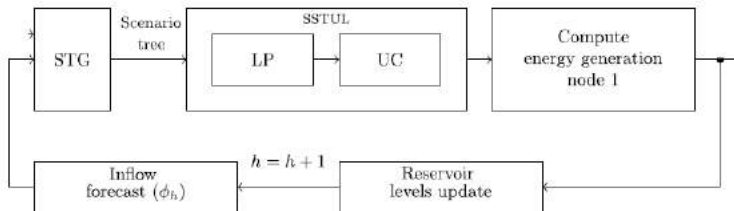
$$q_{min} \leq q_i \leq q_{max}, \quad \forall i \in N,$$

$$v_i, q_i \geq 0, \quad \forall i \in N,$$

Rolling horizon scheme



The stochastic solution provides optimal policies: for each scenario, the solution varies. Rolling horizon schemes are used to "build" the solution.

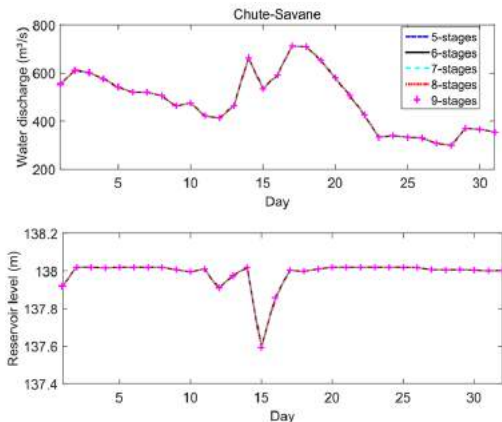


Adapted from Séguin et al. 2017 [23]

Short term optimization



Example of results:



UNIVERSITÉ DE
SHERBROOKE



Séguin et al., 2017[23]



UQAC
Université du Québec
à Chicoutimi

Recap...



Hydropower scheduling is complex and requires many interactions:

- ▶ Hydrologists, statisticians: inflow scenarios
- ▶ Operations research: mathematical formulations
- ▶ Programmers: implementation of the models
- ▶ Analysts & engineers: Final decision

It is a rich and various field to study and/or work in!
Do not hesitate to contact me: sara.seguin@uqac.ca

SOME RESOURCES TO GO FURTHER



UNIVERSITÉ DE
SHERBROOKE



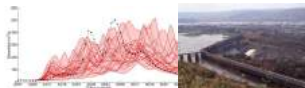
GERAD

GROUP FOR RESEARCH
IN DECISION ANALYSIS

UQAC

Université du Québec
à Chicoutimi

References I



Richard Bellman.

Dynamic programming.
Science, 153(3731):34–37, 1966.



M. M. Belsnes, O. Wolfgang, T. Follestad, and E. K. Aasgård.

Applying successive linear programming for stochastic short-term hydropower optimization.
Electric Power Systems Research, 130:167 – 180, 2016.



D. P. Bertsekas.

Dynamic programming and optimal control, volume 1.
Athena Scientific Belmont, MA, 1995.



Canadian hydropower association.

Canadian hydro capacity & potential (MW), 2019.
[Online; accessed June 3rd 2019].



K.M. Carsell, N.D. Pingel, and D.T. Ford.

Quantifying the benefit of a flood warning system.
Natural Hazard Review, 5(3):131–140, 2004.



Yin-Yann Chen and Hsiao-Yao Fan.

An application of stochastic programming in solving capacity allocation and migration planning problem under uncertainty.

Mathematical Problems in Engineering, 2015.



P. Côté, D. Haguma, R. Leconte, and S. Krau.

Stochastic optimisation of Hydro-Quebec hydropower installations: a statistical comparison between SDP and SSDP methods.

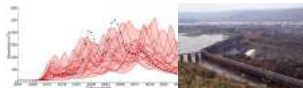
Journal of Civil Engineering, 141(10):427–434, 2017.



UNIVERSITÉ DE
SHERBROOKE



References II



P. Côté and R. Leconte.

Comparison of stochastic optimization algorithms for hydropower reservoir operation with ensemble streamflow prediction.

Journal of Water Resources Planning and Management, 142(2), 2016.



Epex Spot SE.

Bourse de l'électricité epex spot, 2019.

[Online; accessed June 3rd 2019].



B. A. Faber and J. R. Stedinger.

Reservoir optimization using sampling sdp with ensemble streamflow prediction (esp) forecasts.

Journal of Hydrology, 249(1):113–133, 2001.



T. Follestad, O. Wolfgang, and M. M. Belsnes.

An approach for assessing the effect of scenario tree approximations in stochastic hydropower scheduling models.

In Proc. of the 17th Power System Computation Conference, pages 271–277, 2011.



J. Garcia-Gonzalez and G. A. Castro.

Short-term hydro scheduling with cascaded and head-dependent reservoirs based on mixed-integer linear programming.

In Power Tech Proceedings, 2001 IEEE Porto, volume 3, page 6 pp., 2001.



T. Gneiting, F. Balabdaoui, and A.E. Raftery.

Probabilistic forecasts, calibration and sharpness.

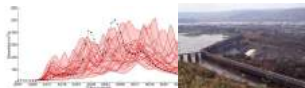
Journal of the Royal Statistical Society B, 70(4):243–268, 2007.



UNIVERSITÉ DE
SHERBROOKE



References III



I.-J. Good.

Rational decisions.

Journal of the Royal Statistical Society, Series B, 14:107–114, 1952.



I. Griva, S. G. Nash, and A. Sofer.

Linear and nonlinear optimization.

Siam, 2009.



J. Kelman, J. Stedinger, L. Cooper, E. Hsu, and S. Yuan.

Sampling stochastic dynamic programming applied to reservoir operation.

Water Resources Research, 26(3):447–454, 1990.



J. W. Labadie.

Optimal operation of multireservoir systems: State-of-the-art review.

Journal of water resources planning and management, 130(2):93–111, 2004.



X. Li, T. Li, J. Wei, G. Wang, and W. W.-G. Yeh.

Hydro unit commitment via mixed integer linear programming: A case study of the three gorges project, china.

IEEE Transactions on Power Systems, 29(3):1232–1241, May 2014.



J. E. Matheson and R. L. Winkler.

Scoring rules for continuous probability distributions.

Management Science, 22:1087–1096, 1976.



J. Nocedal and S. Wright.

Numerical Optimization.



UNIVERSITÉ DE
SHERBROOKE



UQAC

Université du Québec
à Chicoutimi

UNIVERSITY OF TORONTO, OPERATIONS RESEARCH AND FINANCIAL ENGINEERING, SPRINGER NEW YORK, 2009.

References IV



C. Rougé and A. Tilmant.

Using stochastic dual dynamic programming in problems with multiple near-optimal solutions.
Water Resources Research, 52(5):4151–4163, 2016.



T. Dal' Santo and A. S. Costa.

Hydroelectric unit commitment for power plants composed of distinct groups of generating units.
Electric Power Systems Research, 137:16 – 25, 2016.



Sara Séguin, Charles Audet, and Pascal Côté.

Scenario-tree modeling for stochastic short-term hydropower operations planning.
Journal of Water Resources Planning and Management, 143(12):04017073, 2017.



Sara Séguin, Stein-Erik Fleten, Pascal Côté, Alois Pichler, and Charles Audet.

Stochastic short-term hydropower planning with inflow scenario trees.
European Journal of Operational Research, 259(3):1156–1168, 2017.



Z. K. Shawwash, T. K. Siu, and S. O. Russell.

The BC hydro short term scheduling optimization.
IEEE Transactions on Power Systems, 15(3):1125 – 1131, 2000.



R. Taktak and C. D'Ambrosio.

An overview on mathematical programming approaches for the deterministic unit commitment problem in hydro valleys.
Energy Systems, pages 1–23, 2016.



A. Tilmant, D. Pinte, and Q. Goor.

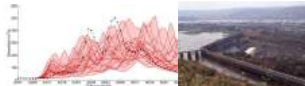
Assessing marginal water values in multipurpose multireservoir systems via stochastic programming.
Water Resources Research, 44(12):W12451, 2008.



UNIVERSITÉ DE
SHERBROOKE



References V



U.S. Forest Service.

What is a watershed?, 2019.
[Online; accessed June 3rd 2019].



Peter Jan Van Leeuwen.

Particle filtering in geophysical systems.
Monthly Weather Review, 137:4089–4114, 2009.



Wikipedia, the free encyclopedia.

Vue du barrage d'inga, 2007.
[Online; accessed June 3rd 2019].



Wikipedia, the free encyclopedia.

Barrage donzère-mondragon bollène vue aérienne, 2010.
[Online; accessed June 3rd 2019].



Wikipedia, the free encyclopedia.

Salle des machines, centrale hydroélectrique de fessenheim, haut-rhin, alsace, france, 2010.
[Online; accessed June 3rd 2019].



D.S. Wilks.

Statistical Methods in the Atmospheric Sciences.
San Diego, 1995.



UNIVERSITÉ DE
SHERBROOKE

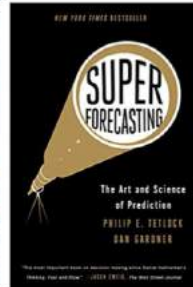
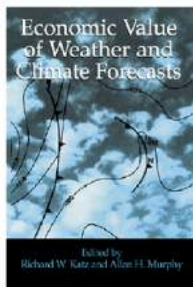
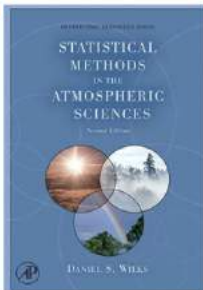
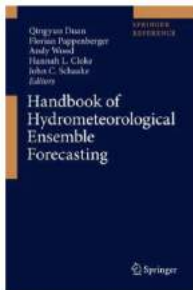


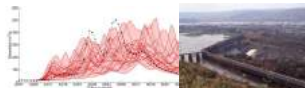
GERAD

GROUP FOR RESEARCH
IN DECISION ANALYSIS

UQAC
Université du Québec
à Chicoutimi

Books





<https://hepex.irstea.fr>

HEPEX

HEPEX BLOG ABOUT HEPEX JOIN & CONTACT RESOURCES WORKSHOPS

HEPEX
A Global Community in Hydrological Ensemble Prediction

OPENIFS@HOME: USING CITIZEN SCIENCE TO IMPROVE OUR UNDERSTANDING OF WEATHER AND HYDROLOGICAL FORECASTS

June 19, 2019 Florian Pappenberger Comment

The history of HEPEX is deeply connected to ensemble forecasting and uncertainty analysis.



@hepexorg