Blackbox Optimization for Chance Constrained Hydro Scheduling Problems

Hydropower Scheduling Workshop, Stavanger, Norway
Computational and Methodological Advances

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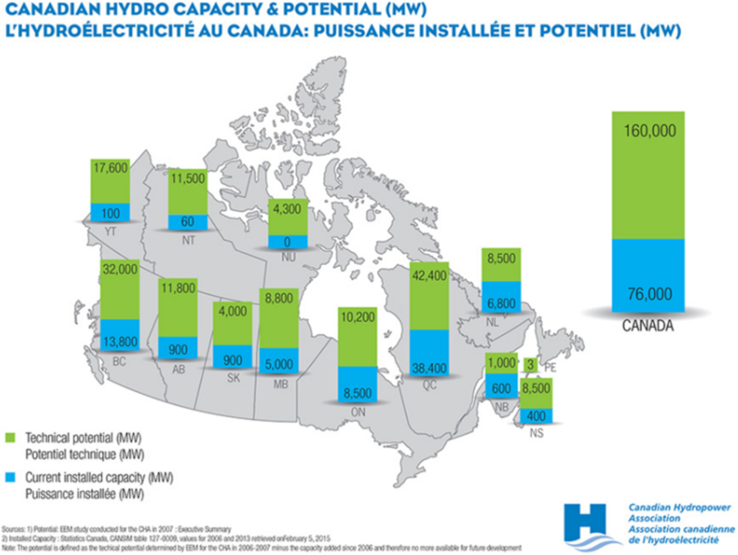
Presentation outline


CANADIAN HYDRO CAPACITY & POTENTIAL (MW)
L'HYDROÉLECTRICITÉ AU CANADA: PUISSANCE INSTALLÉE ET POTENTIEL (MW)
17,600
100
YT
11,500
60
NT
4,300
0
NU
32,000
13,800
BC
11,800
900
AB
4,000
900
SK
8,800
5,000
MB
10,200
8,500
ON
42,400
38,400
QC
8,500
6,800
NL
1,000
600
NB
3
PE
8,500
400
NS
160,000
76,000
CANADA
Technical potential (MW)
Potentiel technique (MW)
Current installed capacity (MW)
Puissance installée (MW)
Sources: 1) Potential: EEM study conducted for the CHA in 2007 : Executive Summary
2) Installed Capacity : Statistics Canada, CANSIM table 127-0009, values for 2006 and 2013 retrieved onFebruary 5, 2015
Note: The potential is defined as the techical potential determined by EEM for the CHA in 2006-2007 minus the capacity added since 2006 and therefore no more available for future development
Canadian Hydropower Association
Association canadienne de l'hydroélectricité

Hydropower optimization

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Reservoir management problem

Determine the water **volumes** of the reservoirs and the **water flows** for each power plants that compose the hydropower system, at every time period to **maximize** the energy production or **minimize** costs.

- When energy prices are not considered, for example in the province of Québec, energy production is maximized.
- When energy prices are considered in a deregulated market, either profit is maximized or costs are minimized.

Reservoir management problem

Difficult to solve since :

- Hydropower production functions are nonlinear and nonconvex
- Uncertain inflows
- Multiple constraints
  - Bounds on reservoir volumes
  - Reservoir levels for dam safety
  - Leisure activities (beaches and navigation requirements)
  - Water flow constraints for environmental protection and flood control
  - Energy production requirements
  - Water balance constraints

Stochastic dynamic programming

Given the uncertainties of the inflows, a **stochastic dynamic programming** algorithm is used to solve the problem.
The expectancy of the energy production is maximized :

$$\max_{q_t^c} \mathbb{E}\left[\sum_{c=1}^{C}\sum_{t=1}^{T} P_t^c(s_t^c, q_t^c, \delta_t^c)\right] \tag{1}$$

$$\text{s.t.} \qquad \text{multiple constraints,}$$

where s_t are the reservoir volumes, q_t the water discharges, δ_t the inflows, $P_t^c(\cdot)$ the hydropower production functions, T the time periods and C the power plants.

Stochastic dynamic programming

The stochastic nature of the problem and the multiple constraints may prevent the optimization algorithm from finding a feasible solution.

The decision makers know their hydropower system, therefore if the policy is simulated over the history of inflows and that they know that there were x very dry (or wet) years, it could be acceptable to violate some constraints given a certain probability.

Chance constraints

Chance constraints, or probabilistic constraints, allow the violation of the constraint given a certain probability.
In this specific case, constraints that can be violated given a certain probability are :

- Minimum energy production
- Maximum flow to avoid downstream flooding
- Minimum environmental flow

Note : The history of inflows is used to validate the optimization model.

Chance constraints

In practice, a penalty parameter is added to the objective function to account for the probability of the constraint to be violated.

$$\max_{u_t} \mathbb{E}[\sum_{t=1}^{T} P_t(s_t, u_t, v_t, q_t) - \chi_1(v_{1,t}^{min} - v_{1,t}) - \chi_2(v_{1,t} - v_{1,t}^{max}) - \chi_3(P_t^{min} - P_t)] \quad (2)$$

s.t

$$\Pr\left(v_{1,t} < v_{1,t}^{min}\right) \leq \xi_{1,t},\ \forall t \in 1, 2, \ldots, T, \quad (3)$$

$$\Pr\left(v_{1,t} > v_{1,t}^{max}\right) \leq \xi_{2,t},\ \forall t \in 1, 2, \ldots, T, \quad (4)$$

$$\Pr\left(P_t < P_t^{min}\right) \leq \xi_{3,t},\ \forall t \in 1, 2, \ldots, T. \quad (5)$$

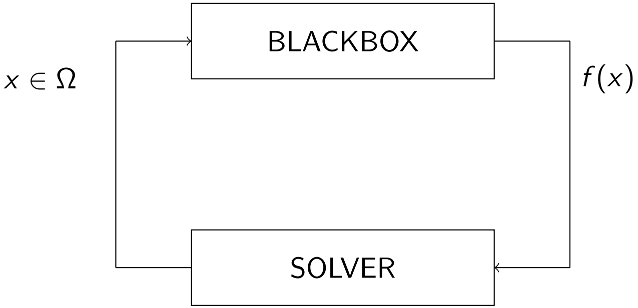
Parameters

- The policy is different for every scenario, therefore, the parameters χ are proper to a scenario.
- A set of parameters that fits all of the scenarios has to be found in order to find an optimal policy.
- We propose an automatic adjustment of the parameters using a **blackbox optimization framework**.

Blackbox optimization

Targets problems in which the objective function and/or the constraints can only be computed by a computer code.

$$\min_{x \in \Omega} f(x) \tag{6}$$



Blackbox optimization

Audet, C., & Dennis Jr, J. E. (2006). Mesh adaptive direct search algorithms for constrained optimization. SIAM Journal on optimization, 17(1), 188-217.

- A budget of evaluations is provided to the blackbox.
- Coordinate search and GPS are MADS ancestors.

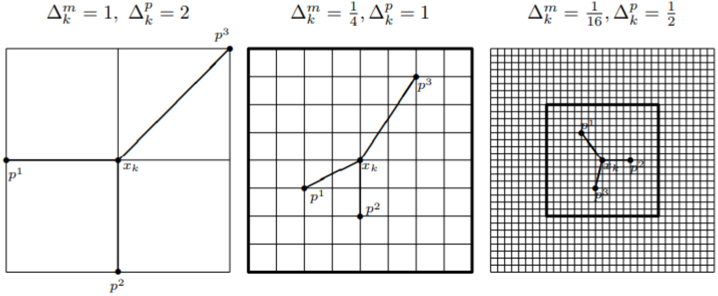


FIG. 4.1. *Example of frames* $P_k = \{x_k + \Delta_k^m d : d \in D_k\} = \{p^1, p^2, p^3\}$ *for different values of* Δ_k^m *and* Δ_k^p. *In all three figures, the mesh* M_k *is the intersection of all lines.*

Blackbox formulation of the reservoir management problem

The reservoir management problem is formulated as the blackbox. Decision variables are χ, the different penalties associated with the chance constraints.

Two sets of scenarios are used :

- **Calibration set.** The reservoir management problem is solved to find the values of the parameters (decision variables) χ.
  - 500 synthetic scenarios
- **Validation set.** The policy is simulated over this set to evaluate the robustness of the optimal penalty parameters.
  - 63 scenarios, which are the actual history

Blackbox formulation of the reservoir management problem

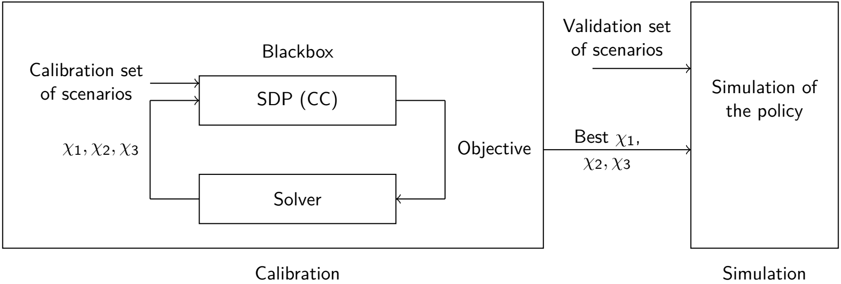
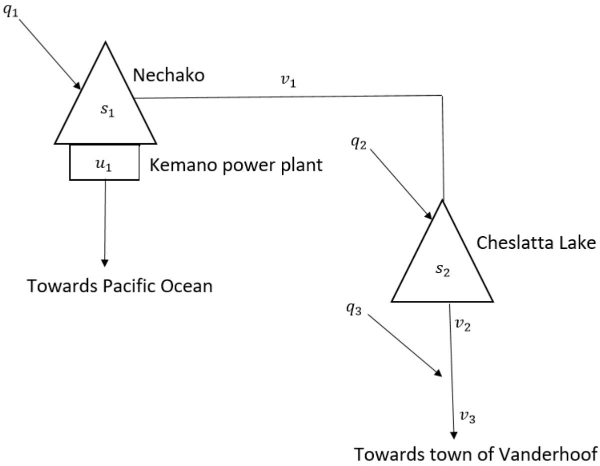


FIGURE – Calibration and simulation process

Nechako hydropower system



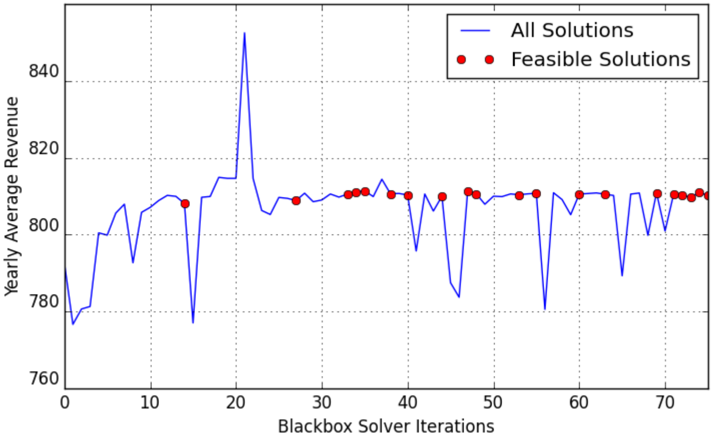
Results - preliminary

Five test runs have been conducted.

Preliminary results :

Subset	Yearly Average Objective Function	Total number of CC Violated	Number of Scenarios	Average computation time in sec.
Calibration	820 $	(0, 0, 0)	500	15482
Validation	826 $	(0, 0, 5)	63	<1

Results - preliminary



Results

- Although constraints are violated, the blackbox solver helps improve the objective function.
- A feasible solution is found on the calibration set.
- Extensive tests will be carried out to improve the robustness of the optimal parameters.
  - Number of scenarios in each set (calibration, validation).
  - Generation of the synthetic scenarios.

Concluding remarks

- Reservoir management problem is formulated with chance constraints.
- A blackbox optimization framework is used to find the optimal values of the parameters, using a calibrating set of scenarios.
- The policies obtained are simulated on the history of inflows, on the validating set of scenarios.
- Future work : choice of the calibrating set of scenarios and testing.

Contact

Tusen takk !

Do not hesitate to contact me :

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