Using efficiency points to maximize energy generation in the short-term hydro-scheduling problem

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Presentation outline

1. Short-term hydropower optimization
2. Project
   - Hydropower system
   - Short-term hydropower scheduling
3. Methodology
   - Approximation of the hydropower production functions
   - Optimization model
   - Mathematical comparison of 2 scenario tree generation methods
   - Numerical results
4. Concluding remarks

Project

This project is part of Maissa Daadaa's Ph.D. thesis. Co-advisors are Miguel F. Anjos (University of Edinburgh) and Kenjy Demeester (Rio Tinto).

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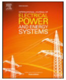

An optimization model to maximize energy generation in short-term hydropower unit commitment using efficiency points

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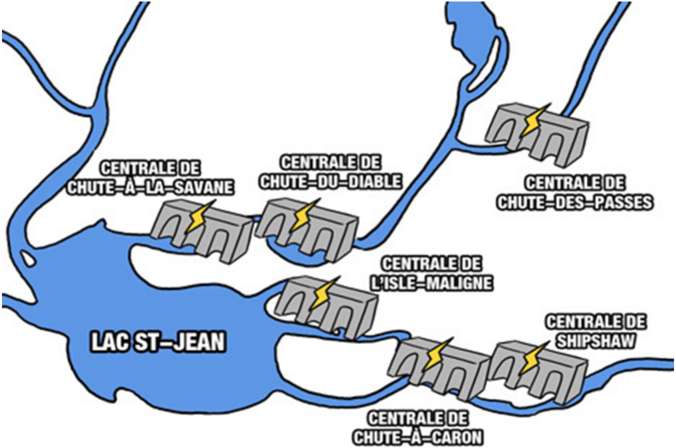
Hydropower system

Two powerplants from Rio Tinto are used to assess the methodology.



Short-term optimization model

In this project, we are interested in the short-term optimization model.

We aim at taking decisions on :

- Water discharge
- Reservoir volume
- State of turbines

for a given planning horizon.

Short-term hydropower scheduling

Purpose :

- Maximize the produced energy.
- Imposition of max. 2 startups per 10 days.

Other considerations :

- Calculation times.
- Multiple **inflow** scenarios.
- Solution directly usable in practice.

Questions :

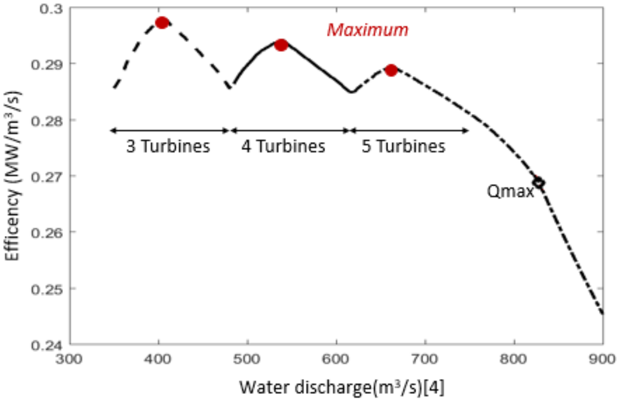
1. Is the solution of the optimization affected by the scenario tree method ?
2. Are scenarios required ?

Methodology

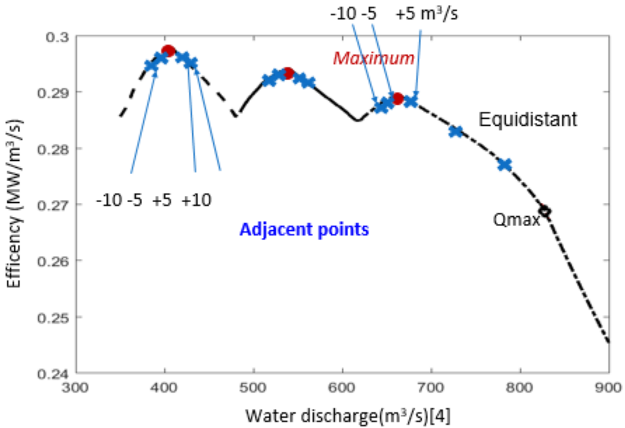
In order to answer the proposed questions, the following methodology is proposed.

1. Approximation of the hydropower production functions
2. Mathematical comparison of 2 scenario tree generation methods
   - Backward scenario tree with Scenred.
   - Neural gaz scenario tree generation method.
3. Numerical results on real test cases using both scenario tree methods for the short-term optimization.

Approximation of the hydropower production functions

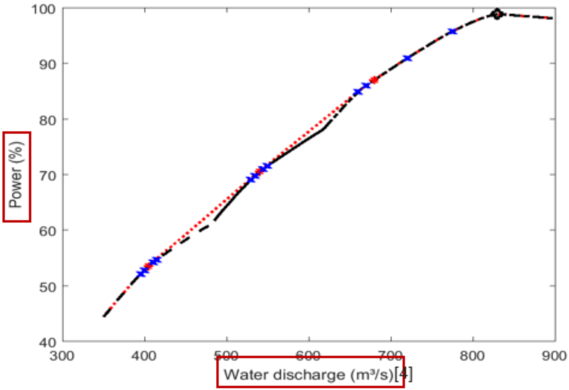


Approximation of the hydropower production functions



Approximation of the hydropower production functions

A pair of maximum efficiency points of water discharge and power



Optimization model

❖ ***Objective function :***

The objective is to maximize total energy production in stage 0 and expected energy production stages

$$max_{y,v,z}[\sum_{c\in C}\sum_{b\in B}\sum_{k\in K_b^c} P_{k,0}^c \times y_{k,0}^c - \sum_{c\in C}\theta^c \times (V_{max}^c - v_0^c) - \sum_{c\in C}\sum_{j\in J_0}\varepsilon^c \times z_{j,0}^c +$$

$$\sum_{c\in C}\sum_{i\in I}\sum_{b\in B}\sum_{k\in K_b^c} P_{k,i}^c \times y_{k,i}^c - \sum_{c\in C}\sum_{i\in I}\theta^c \times (V_{max}^c - v_i^c) - \sum_{c\in C}\sum_{i\in I}\sum_{j\in J_i}\varepsilon^c \times z_{j,i}^c +$$

$$\Delta_t \times [\sum_{s\in S}\pi_s \times [\sum_{c\in C}\sum_{n\in N_s}\sum_{b\in B}\sum_{k\in K_b^c} P_{k,n}^c \times y_{k,n}^c - \sum_{c\in C}\sum_{n\in N_s}\theta^c \times (V_{max}^c - v_n^c) - \sum_{c\in C}\sum_{n\in N_s}\sum_{j\in J_n}\varepsilon^c \times z_{j,n}^c]] \quad (1)$$

Probability

Optimization model cont'd

$$v_{n+1}^c = v_n^c + \Delta_t \times [(\delta_n^c \times \beta) - \sum_{b\in B}\sum_{k\in K_b^c}(q_{n,k}^c \times y_{k,n}^c \times \beta) - (d_n^c \times \beta) + \sum_{l\in U^c}\sum_{b\in B}\sum_{k\in k_b^l}(q_{n,k}^l \times y_{k,n}^l \times \beta) + (d_n^l \times \beta)] \quad ,\forall c\in C, \forall n\in N_s, \forall s\in S \quad (2)$$

Water balance

$$\sum_{b\in B}\sum_{k\in K_b^c} y_{k,n}^c = 1 \quad ,\forall c\in C, \forall n\in N_s, \forall s\in S \quad (3)$$

$$\sum_{b\in B}\sum_{k\in K_b^c} y_{k,n+1}^c \times A_{n+1,k,j}^c - \sum_{b\in B}\sum_{k\in K_b^c} y_{k,n}^c \times A_{n,k,j}^c \leq z_{j,n}^c \quad ,\forall c\in C, \forall n\in N_s, \forall s\in S \forall j\in J_n, \quad (4)$$

Combination turbines

$$\sum_{s\in S}\sum_{n\in N_s}\sum_{j\in J_n} z_{j,n}^c \leq N_{max}^c \quad ,\forall c\in C, \quad (5)$$

Startups

$$v_{min}^c \leq v_n^c \leq V_{max}^c \quad ,\forall c\in C, \forall n\in N_s, \forall s\in S \quad (6)$$

$$v_0^c = v_{ini}^c \quad ,\forall c\in C, \quad (7)$$

$$v_{N_s}^c \geq v_{final}^c \quad ,\forall c\in C, \quad (8)$$

$$y_{k,n}^c, y_{k,n}^l, z_{j,n}^c \in \mathcal{B} \quad ,\forall c\in C, \forall n\in N_s, \forall n\in N_s, \forall b\in B^c, \forall k\in K_b^c, \forall l\in U^c \quad (9)$$

$$d_n^c, d_n^l, v_n^c \in \mathcal{R}^+ \quad ,\forall c\in C, \forall n\in N_s, \forall l\in U^c. \quad (10)$$

Bounds

Validation

The determinisitc model was compared to real operational decisions.

Results show that :

- For the 65 instances, the model allows to produce more energy.
- The proposed solutions are always on the efficiency points, where the engineers want to operate the power plants.
- The solution can be directly implemented in practice.

Mathematical comparison of scenario tree generation methods

Is the solution of the optimization affected by the scenario tree method ?

Mathematical comparison of scenario tree generation methods

Two methods are compared :

- Backward reduction. Delete scenarios from full tree to minimize probability distance between reduced tree and full tree.
  $\rightarrow$ Structure of the tree varies. Implementation with Scenred.
- Neural gaz. Competitive learning method that updates the values of the nodes to gradually reduce distance of the full tree and reduced tree.
  $\rightarrow$ Structure of the tree is preserved. In-house implementation.

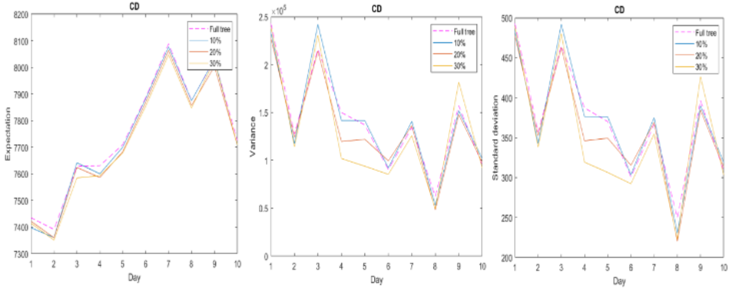
Mathematical comparison of scenario tree generation methods

Main takeaways :

- Results were tested on 4 months of inflow scenarios.
- Different % of reduction for backward method. Expectation, variance and standard variation preserved until 20 %.
- Only the expectation preserved with neural gaz method.

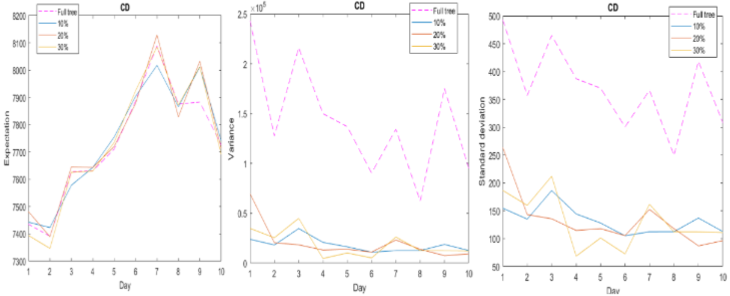
Mathematical comparison of scenario tree generation methods

Example of results for backward method :



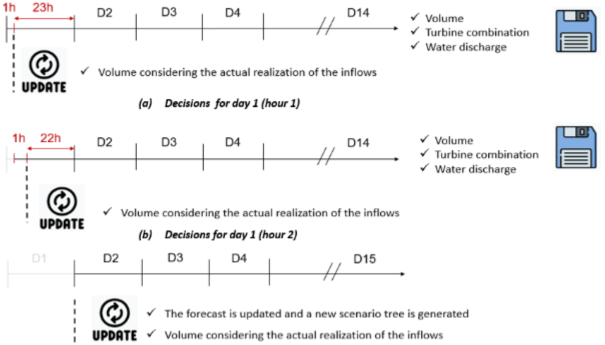
Mathematical comparison of scenario tree generation methods

Example of results for neural gas method :

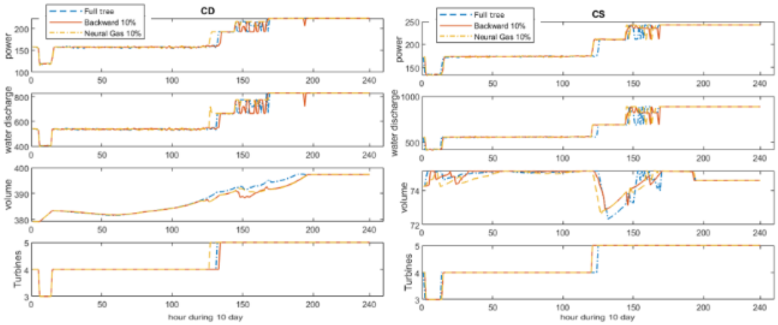


Rolling horizon

The stochastic short-term hydropower optimization problem is tested in a rolling horizon fashion.



Operational results



Comparison of the solutions for backward, neural gas methods and the full tree in December with 10% of reduction

Numerical results

- The solutions proposed by the 2 scenario tree generation methods are similar when reduction is below 10%.
- When variability in the inflows is low, the median scenario allows to obtain good results.
- Results are obtained faster with the neural gaz method, but variance is not preserved, which is usually not a problem with low variability.

Concluding remarks

- In this project, efficiency curves were used to force the model to work on efficiency points.
- Two methods of scenario tree generation were compared to see the effect on the preservation of the mathematical aspects, but also operational aspects of the solution.
- The proposed solution can be used directly and a maximal number of startups was imposed to stick to usual operations.

Contact

Tusen takk !

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