Decision support model for weekly operation of hydroelectric reservoirs by stochastic nonlinear optimization

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- Introduction
- System modeling
- Model description
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- Conclusions
Renascence of hydro scheduling models

• **Nowadays**, under a deregulated framework electric companies manage their own generation resources and need detailed operation planning tools.

• In the next future, high penetration of intermittent generation is going to force the electric system operation.

• Hydro and storage hydro plants are going to play a much more important role due to their flexibility and complementary use with intermittent generation.
Medium term model (i)

- Hydroelectric model deals only with hydro plants
- Hydrothermal model manages simultaneously both hydro and thermal plants
- Thermal units considered individually. So rich marginal cost information for guiding hydro scheduling
- No aggregation or disaggregation process for hydro input and output is needed
- It is very difficult to obtain meaningful results for each hydro plant because it requires a huge amount of data and the complexity of hydro subsystems
Medium term model (ii)

• Determines:
  – the optimal yearly operation of all the thermal and hydro power plants
  – taking into account multiple basins and multiple cascaded reservoirs connected among them

• Cost minimization model because the main goal is medium term hydro operation
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Demand

- Weekly demand with two load levels (peak and off-peak each week)
Hydro subsystem

- Different modeling approach for hydro reservoirs depending on:
  - Owner company
  - Relevance of the reservoir
- Reservoirs belonging to other companies modeled in energy units [GWh]
- Own reservoirs modeled in water units [hm$^3$, m$^3$/s]
- Important reservoirs modeled with water head effects
- Very diverse system:
  - Hydro reservoir volumes from 0.15 to 2433 hm$^3$
  - Hydro plant capacity from 1.5 to 934 MW
Stochasticity sources

- Natural hydro inflows (clearly the most important factor in Spanish electric system)

<table>
<thead>
<tr>
<th>Year</th>
<th>Hydro energy Available [TWh]</th>
<th>Index</th>
<th>Probability of being exceeded [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001</td>
<td>32.9</td>
<td>1.13</td>
<td>32</td>
</tr>
<tr>
<td>2002</td>
<td>20.9</td>
<td>0.72</td>
<td>87</td>
</tr>
<tr>
<td>2003</td>
<td>33.2</td>
<td>1.15</td>
<td>30</td>
</tr>
<tr>
<td>2004</td>
<td>22.7</td>
<td>0.79</td>
<td>80</td>
</tr>
<tr>
<td>2005</td>
<td>12.9</td>
<td>0.45</td>
<td>100</td>
</tr>
<tr>
<td>2006</td>
<td>24.0</td>
<td>0.83</td>
<td>70</td>
</tr>
</tbody>
</table>

- Changes in reservoir volumes are significant because of:
  - stochasticity in hydro inflows
  - chronological pattern of inflows and
  - capacity of the reservoir with respect to the inflows
Historical natural inflows

Week

Natural Inflows [m³/s]

1975
1976
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
Scenario tree generation

- A multivariate scenario tree is obtained by neural gas clustering technique that simultaneously takes into account the main stochastic series and their spatial and temporal dependencies.
- Very extreme scenarios can be artificially introduced with a very low probability.
- Number of scenarios generated enough for yearly operation planning.
Natural inflows: scenario tree

[Graph showing natural inflows over weeks for different series]
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Constraints: Generation and load balance

\[
\text{Generation of thermal units} \quad + \quad \text{Generation of hydro units} \\
- \quad \text{Consumption of storage hydro units} \\
= \quad \text{Demand}
\]
Constraints: Minimum and maximum operating hours of thermal units

- Introduced to model:
  - Unavailability of thermal units
  - Domestic coal subsidies
  - CO2 Emission allowances
  - Capacity payments

- They are not separable by period

\[
\text{minimum} \leq \text{Yearly operation hours of each thermal unit for each scenario} \leq \text{maximum}
\]

\[
\text{minimum} \leq \text{Average yearly operation hours of each thermal unit} \leq \text{maximum}
\]
Constraints: Water balance

Reservoir volume at the beginning of the period
+ Natural inflows
− Spills from the own reservoir
+ Spills from upstream reservoirs
+ Turbined water from upstream hydro plants
+ Pumped water from downstream hydro storage plants
− Turbined and pumped water from the own reservoir
= Reservoir volume at the end of the period
Constraint: Water head effects

• Power generation is the product (nonlinear function) of the flow and the production function

\[ P = Q \times PF \]

• Production function \( PF \) depends linearly on water head

\[ PF = \alpha H_p \]
Constraint: Volume as a function of the head

- Reservoir volume depends quadratically (nonlinearly) on water head

\[ V = \beta + \beta' H_r + \beta'' H_r^2 \]
Constraint: Water heads

Water head of the reservoir = forebay level – reference level

Water head of the plant = forebay level of the reservoir – tailrace level of the plant

Tailrace level of the plant = \max [forebay level of downstream reservoir, reference tailrace level of the plant]
Constraint: operation limits

Reservoir volumes between limits for each hydro reservoir

Power operation between limits for each unit
Multiobjective function

• Thermal plant variable costs

• Penalties introduced in the objective function for softening several additional constraints:
  – Final reservoir volumes
  – Exceeding operating rule curves (minimum and maximum)
  – Minimum and maximum yearly operation hours of thermal units
Type of optimization problem

- **Deterministic approaches:**
  - Network Flows
  - LP
  - NLP
  - MILP
    - commitment of thermal or hydro units
    - piecewise linear approximation of water head effects

- **Stochastic approaches:**
  - Stochastic Dynamic Programming (SDP)
  - Stochastic Linear Programming. Decomposition approaches (Benders, Lagrangean Relaxation, Stochastic Dual Dynamic Programming)
  - Stochastic Nonlinear Programming
Solution algorithm

• Algorithm:
  – Successive LP
  – Direct solution by a NLP solver

• Very careful implementation
  – Scaling of variables
  – Use of simpler expressions
  – Initial values and bounds for all the nonlinear variables computed from the solution provided by linear solver CPLEX 10.2 IPM
  – Nonlinear solver CONOPT3
Model implementation

- General hydro topology
- Spreadsheet-based graphical interface
- GAMS-based optimization model
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Case study

- **Spanish electric system**
  - 130 thermal units
  - 3 main basins with 50 hydro reservoirs/plants and 2 pumped storage hydro plants
  - 16 scenarios

- **Problem size:**
  - 271887 constraints
  - 442239 variables
  - 1611184 non zero elements
  - 12832 nonlinear variables
  - 8020 nonlinear constraints
Hydro plant operation

- Relative error in the energy generated for each hydro plant between LP and NLP approaches
Hydro reservoir operation (i)

LP solution

NLP solution
Hydro reservoir operation (ii)

- **LP solution**
- **NLP solution**
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Summary

- Medium term hydrothermal model

- Nonlinear water head effects modeled for relevant reservoirs

- Stochastic nonlinear optimization problem solved directed by a nonlinear solver given a close initial solution provided by a linear solver
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