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COMPARING SSDP WITH STANDARD WATER VALUE CALCULATION ON TYPICAL NORDIC HYDRO SYSTEMS

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Outline

- Introduction
- Sampling Stochastic Dynamic Programming
- Implementation and Cases
- Results
- Conclusion and Discussion

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Based on previous work

1. Kelman, J., et al., *Sampling stochastic dynamic programming applied to reservoir operation.* Water Resources Research, 1990. **26**(3): p. 447-454.
2. Faber, B.A. and J.R. Stedinger, *Reservoir optimization using sampling SDP with ensemble streamflow prediction (ESP) forecasts.* Journal of Hydrology, 2001. **249**(1–4): p. 113-133.

Introduction

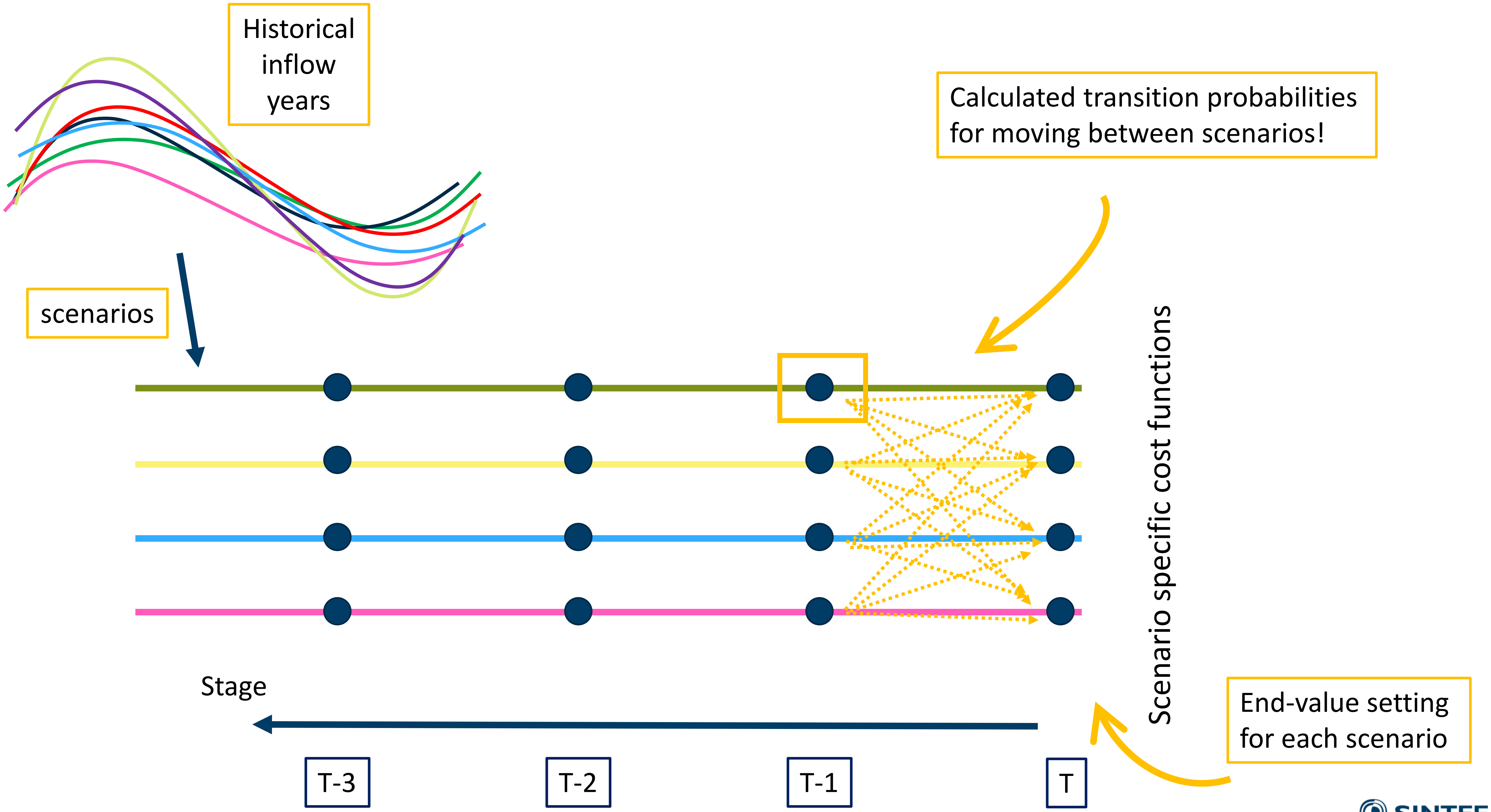
Objective: To apply the SSDP method to typical Norwegian hydropower optimization problems and compare the results with a similar implementation of the water value method (i.e. stochastic dynamic programming).

Hypothesis: Improved representation of extreme weather years should give a better evaluation of severity of such years and improved operation of the hydro power reservoirs, lower operational costs and less curtailment.

Sampling Stochastic Dynamic Programming

Based on SDP, the main differences are that we in SSDP:

1) use historical weather years (inflow) directly as scenarios
2) calculates deterministic cost function for each scenario (year), which are used to estimate the future cost


Historical inflow years
Calculated transition probabilities for moving between scenarios!
scenarios
Scenario specific cost functions
Stage
End-value setting for each scenario
T-3
T-2
T-1
T

(1) $$f_t(S_t) = \min_{R_t} \{C_t\left(S_t, Q_t^i, R_t\right) + E_{j|i}[f_{t+1}(S_{t+1}, j)]\}$$

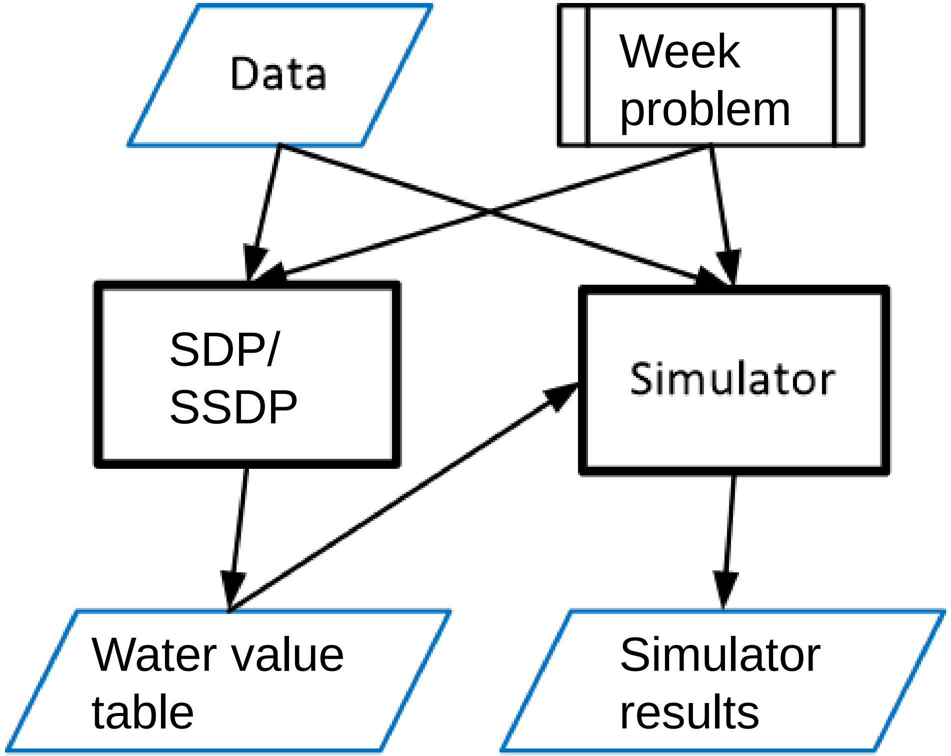
(2) $$f_t(S_t, i) = C_t\left(S_t, Q_t^i, R_t\right) + f_{t+1}(S_{t+1}, i)$$

(3) $$E_{j|i}[f_{t+1}(S_{t+1}, j)] = \sum_{\mathrm{j} \in M} P_t(j|i)\ [f_{t+1}(S_{t+1}, j)]$$

Implementation: model

Similar model for SDP and SSDP

- Equal formulation of the decision problem
- Water value calculation (optimisation) and simulation
- Optimisation and simulation on same scenarios
- SSDP method based on (Kelman, 1990) and (Faber, 2001)
- SDP model based on (Helseth, 2017)



Implementation: the decision problem

Objective function: Minimise total socioeconomic cost

Such that:

Supply meets demand (marked balance: dual = power price)

The reservoir balance is maintained (dual = water value)

Max exchange capacity is honoured

Max production capacity of the generators are honoured

Includes: one hydro power generator with reservoir, one thermal generator, one "ration generator" and exchange/trade to a market with exogenously given price. Inflow is stochastic.

Linear problem, no head effects, no start/stop costs or ramping.

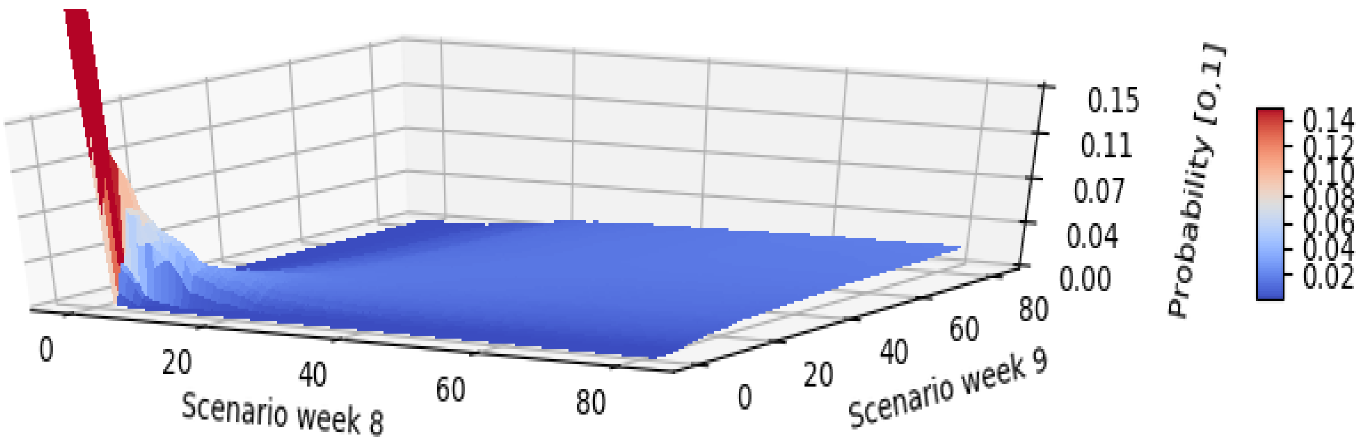
Equal probabilities for moving between scenarios in the SDP model (No Markov model or correlation)

Calculated transition probabilities for moving between the scenarios in the SSDP model

Differences in probabilities

Transition probabilities in SSDP: Probability of moving between scenarios based on inflow calculation uses Bayes theorem

Transition probabilities, sorted from high to low inflow



Cases

- Tested on three separate hydro system cases from Norway
- 1 year time horizon (52 weeks), 83 years of stochastic inflow
- Slack, base and tight cases

	Reservoir size [GWh]	Max discharge [GWh/week]	Average inflow [GWh/yr]	Max inflow [GWh/yr]	Min inflow [GWh/yr]
Reg 1	9 361	716	19 089	22 863	11 316
Reg 2	33 330	2015	47 796	76 726	28 113
Reg 3	11 650	550	13 862	20 657	8 021

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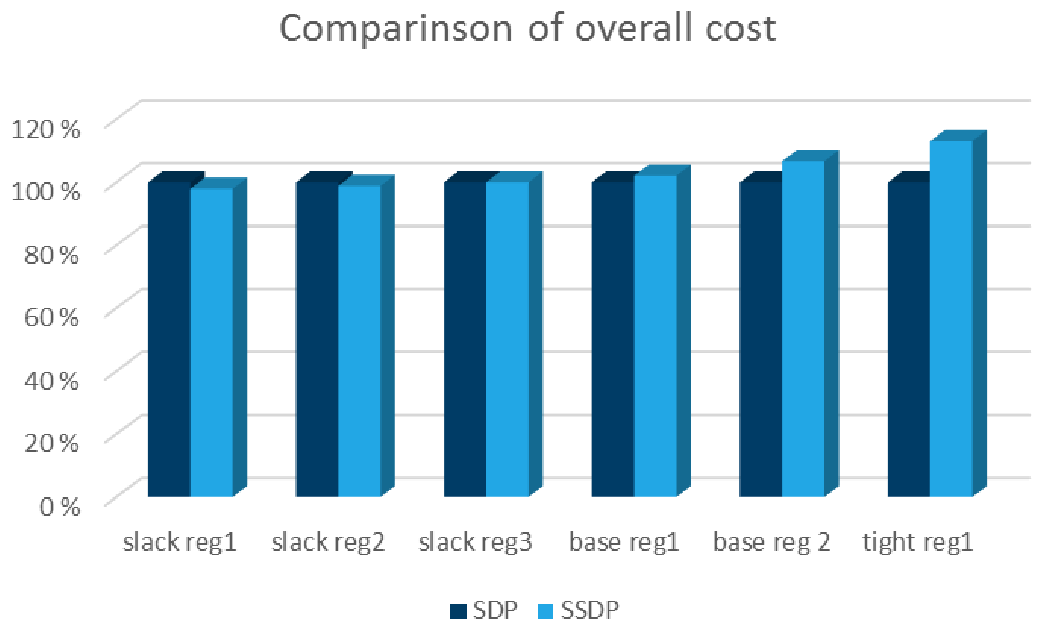
Results

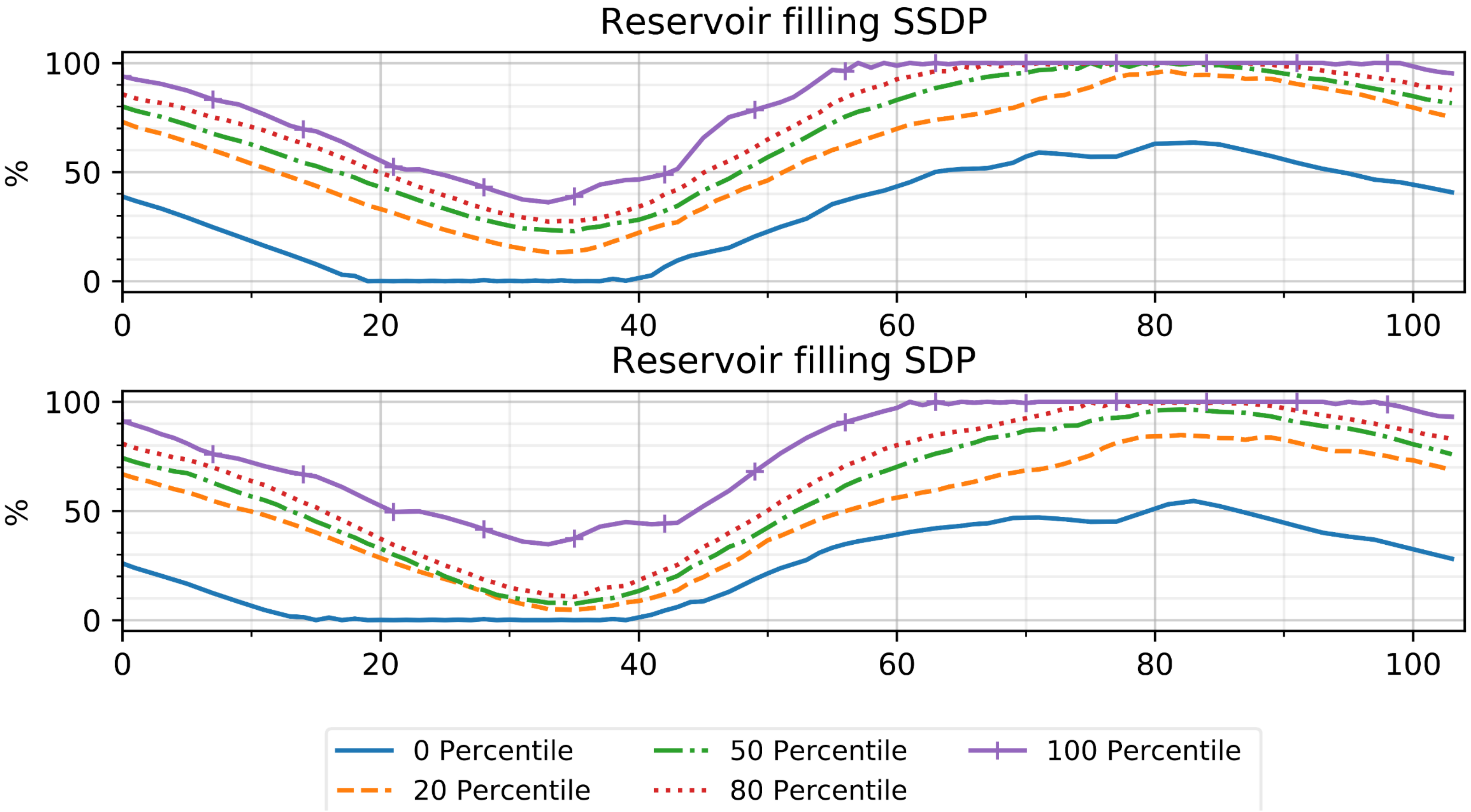
Only minor differences in operational cost in the SSDP and SDP solutions for the slack and base cases for all regions

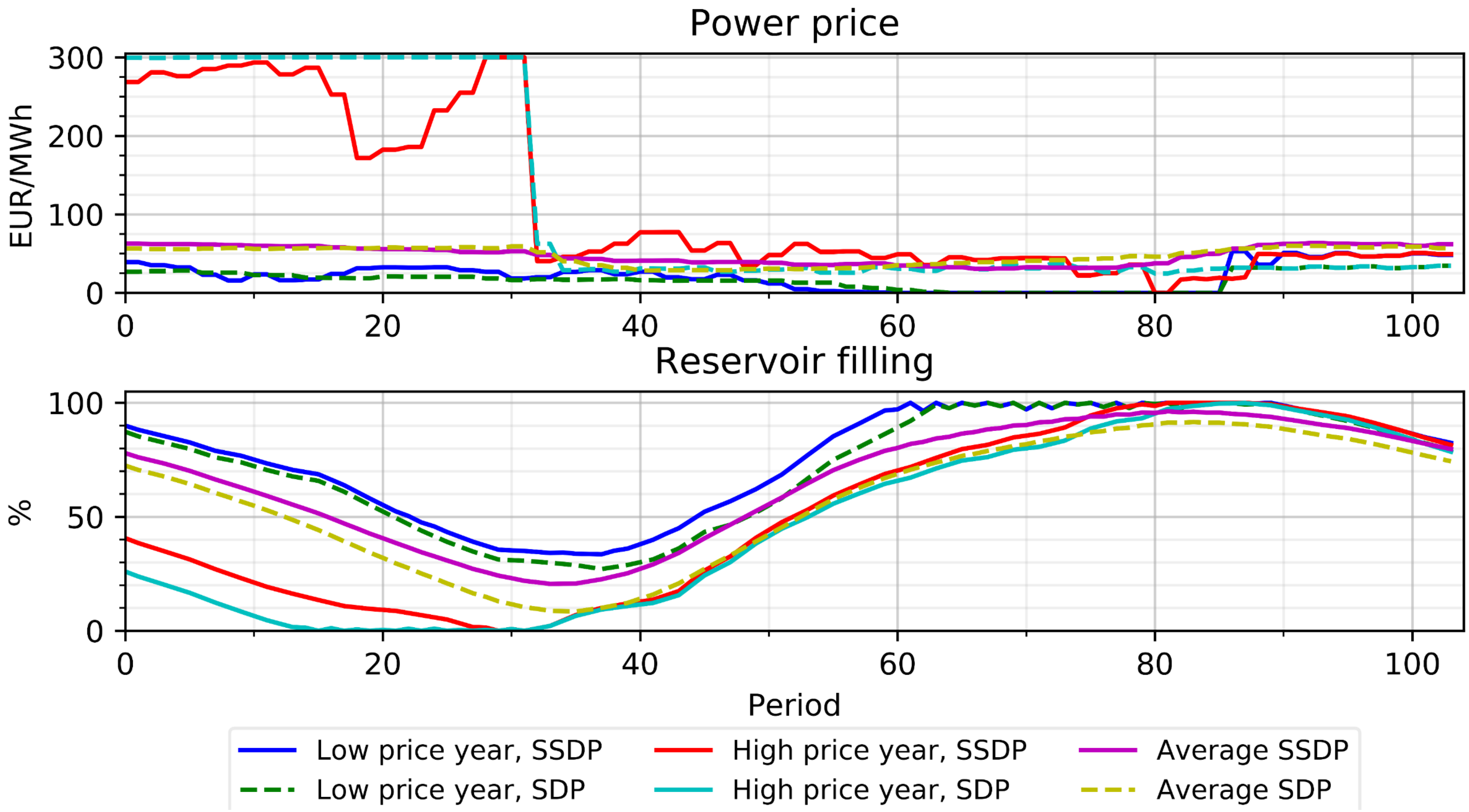


Results Reg 1 tight case

- Higher reservoir filling in SSDP solution
  - Reduced curtailment
  - Increased spillage
  - Overall higher cost

- Different evaluation of the severity of wet versus dry years


Reservoir filling SSDP
%
100
50
0
0
20
40
60
80
100
Reservoir filling SDP
%
100
50
0
0
20
40
60
80
100
0 Percentile
20 Percentile
50 Percentile
80 Percentile
100 Percentile


Power price
EUR/MWh
300
200
100
0
0
20
40
60
80
100
Reservoir filling
%
100
50
0
0
20
40
60
80
100
Period
Low price year, SSDP
Low price year, SDP
High price year, SSDP
High price year, SDP
Average SSDP
Average SDP

Conclusion and discussion

- Hard to conclude that one method is better than the other.
- Considering socioeconomic cost the SSDP model performed worse than the SDP model in the tight case.

Possible improvement: use different/additional hydrological state variable than inflow (i.e. snow storage)

References

1. Kelman, J., et al., *Sampling stochastic dynamic programming applied to reservoir operation.* Water Resources Research, 1990. **26**(3): p. 447-454.
2. Faber, B.A. and J.R. Stedinger, *Reservoir optimization using sampling SDP with ensemble streamflow prediction (ESP) forecasts.* Journal of Hydrology, 2001. **249**(1–4): p. 113-133.
3. Côté, P. and R. Leconte, *Comparison of stochastic optimization algorithms for hydropower reservoir operation with ensemble streamflow prediction.* Journal of Water Resources Planning and Management, 2015. **142**(2): p. 04015046.
4. Helseth, A., et al., *Assessing Hydropower Operational Profitability Considering Energy and Reserve Markets.* IET Renewable Power Generation, 2017. **11**(13): p. 1640-1647.

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Teknologi for et bedre samfunn

(4) $$z_t^i = \frac{(Q_t^i - \overline{Q_t})}{\sigma_t}$$

(5) $$p[z_t | z_{t+1}^j] \sim N(\hat{z}_t(z_{t+1}^j), \sigma_e))$$

(6) $$P_t(\mathrm{j}|\mathrm{i}) = P_t[z_{t+1}^j \, | z_t^i] = \frac{p[z_t^i | z_{t+1}^j] \, P^j}{\sum_{k \in M} p[z_t^i | z_{t+1}^k] P^k}$$