Optimal reservoir operation policies using novel nested algorithms

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Introduction

- Optimal reservoir operation methods include:

  Dynamic programming (DP)

  Stochastic dynamic programming (SDP)

"curse of dimensionality"

the computational complexity with the state – decision space dimension

Successive approximations, incremental dynamic programming and differential dynamic programming

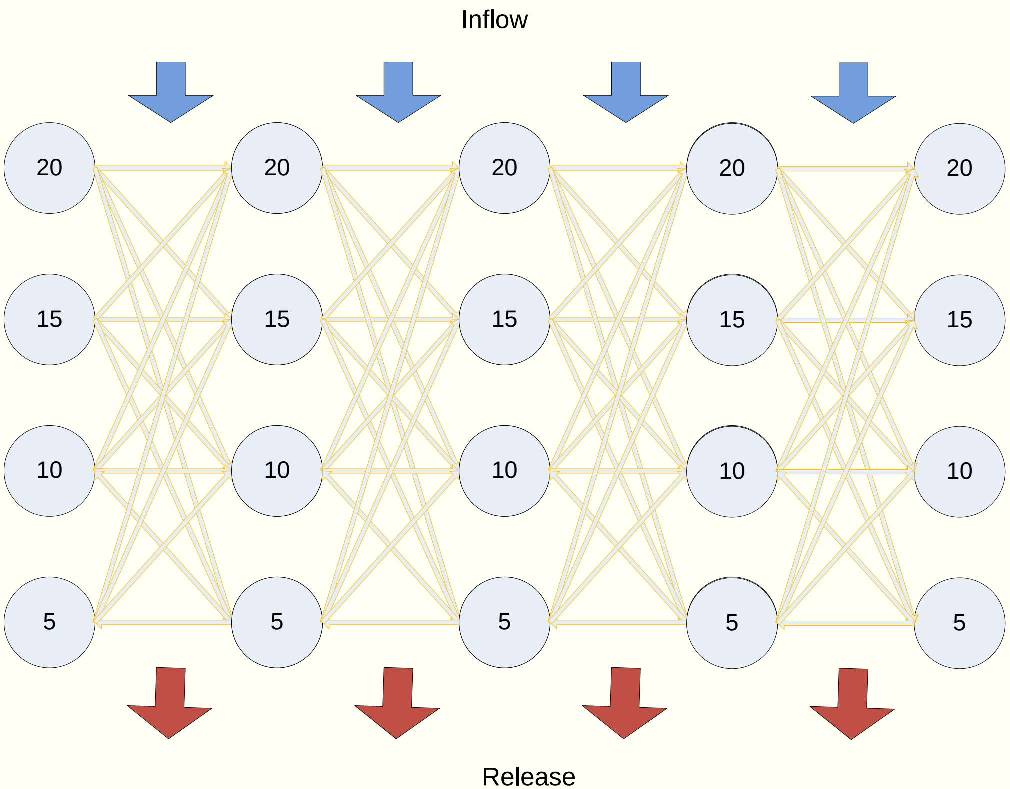
"curse of modelling"

Dynamic programming

$$x_{t+1} = x_t + q_t - r_t - e_t$$ Reservoir model

Bellman equation

$$V_t\left(s_t\right) = \min\left\{g\left(s_t, s_{t+1}, a_t\right) + V_{t+1}\left(s_{t+1}\right)\right\}$$ (for stages *t=T-1,T-2,…1*)



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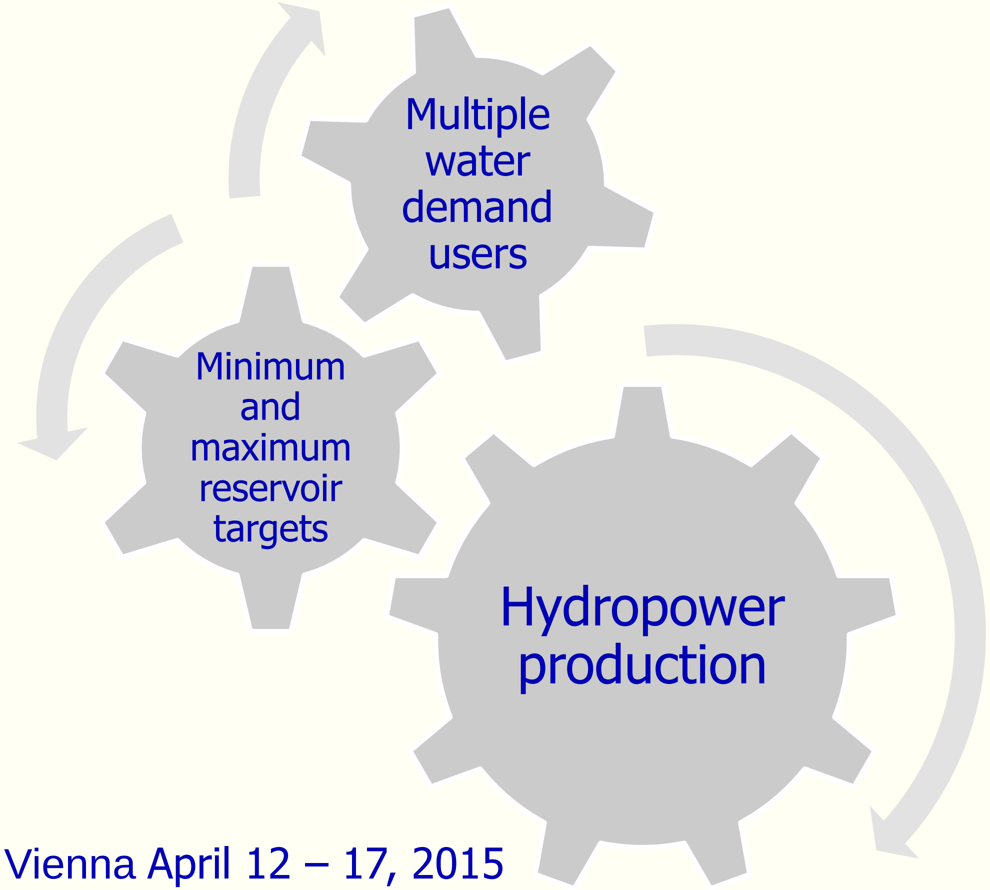
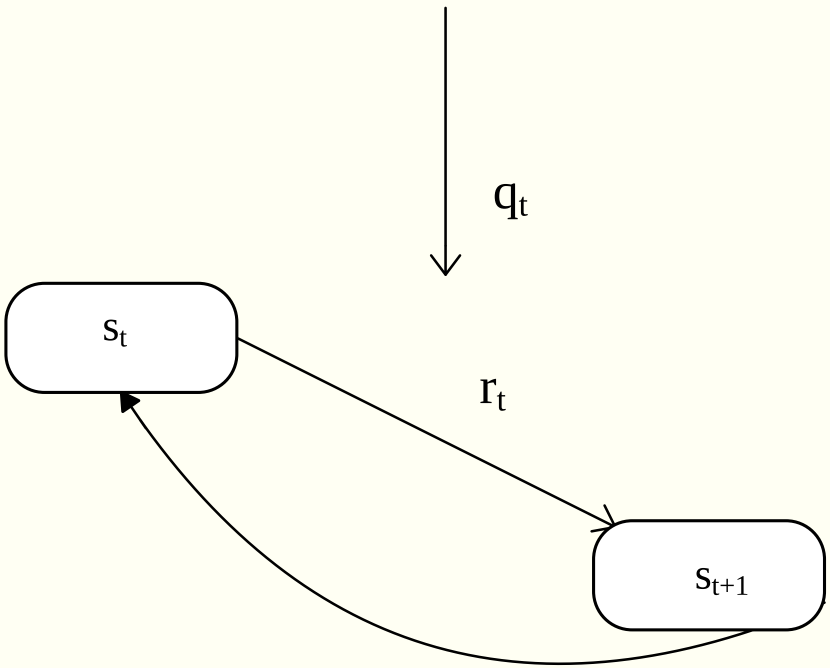
Main question

How to enhance DP/SDP algorithm and develop new algorithm (methodology) that is flexible with including additional objectives like cities water demand, agriculture water demand, ecology water demand, hydro power production and etc., alleviate as much as possible the curse of dimensionality and computational cost?

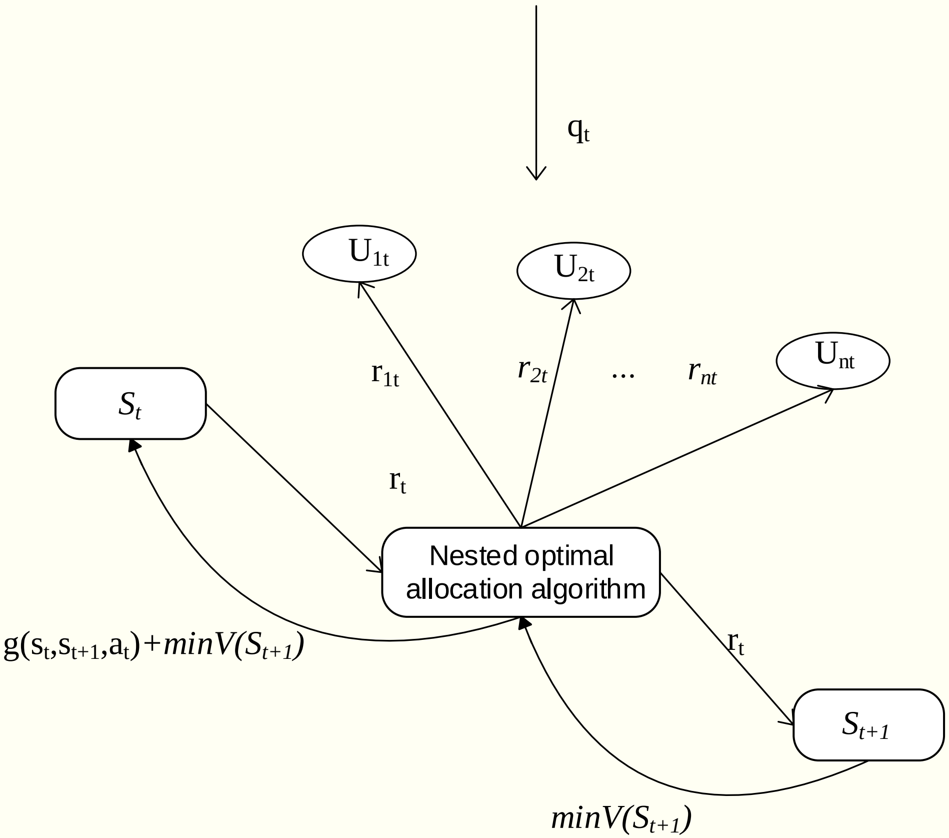


Main idea
nested algorithm

One step of the DP algorithm.



One step of the nDP algorithm



Nested optimal allocation algorithms
Simplex – Quadratic Knapsack

$$r_{1t} + r_{2t} \ldots + r_{nt} \le r_t$$

$$r_{1t} \le d_{1t}, r_{2t} \le d_{2t} .., r_{nt} \le d_{nt}$$

$$r_t, d_{t1}, d_{t2} .., d_{nt} \ge 0$$

$$\min \sum_{i=1}^{n} w_{it} \cdot \left(d_{it} - r_{it}\right)$$

Simplex

$$\min \sum_{i=1}^{n} w_{it} \cdot \left(d_{it} - r_{it}\right)^2$$

Quadratic Knapsack

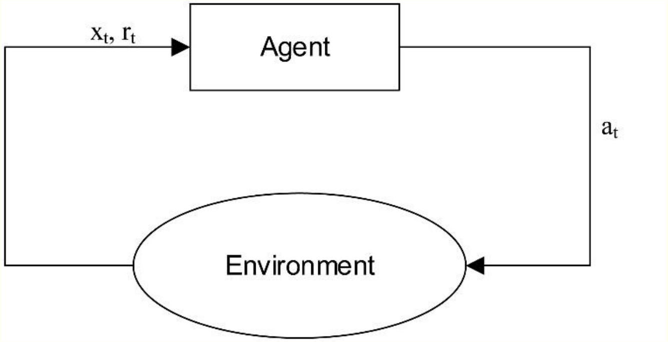
Implementing the idea into nSDP and nRL

- The same idea of nesting optimization algorithm is implemented in nSDP (nested Stochastic dynamic programming)

$$V_t(s_t) = \min\left\{ g(s_t, s_{t+1}, a_t) + \gamma^t \cdot \sum_j p_{q_{t+1}|q_t} \cdot V_{t+1}(s_{t+1}) \right\}$$

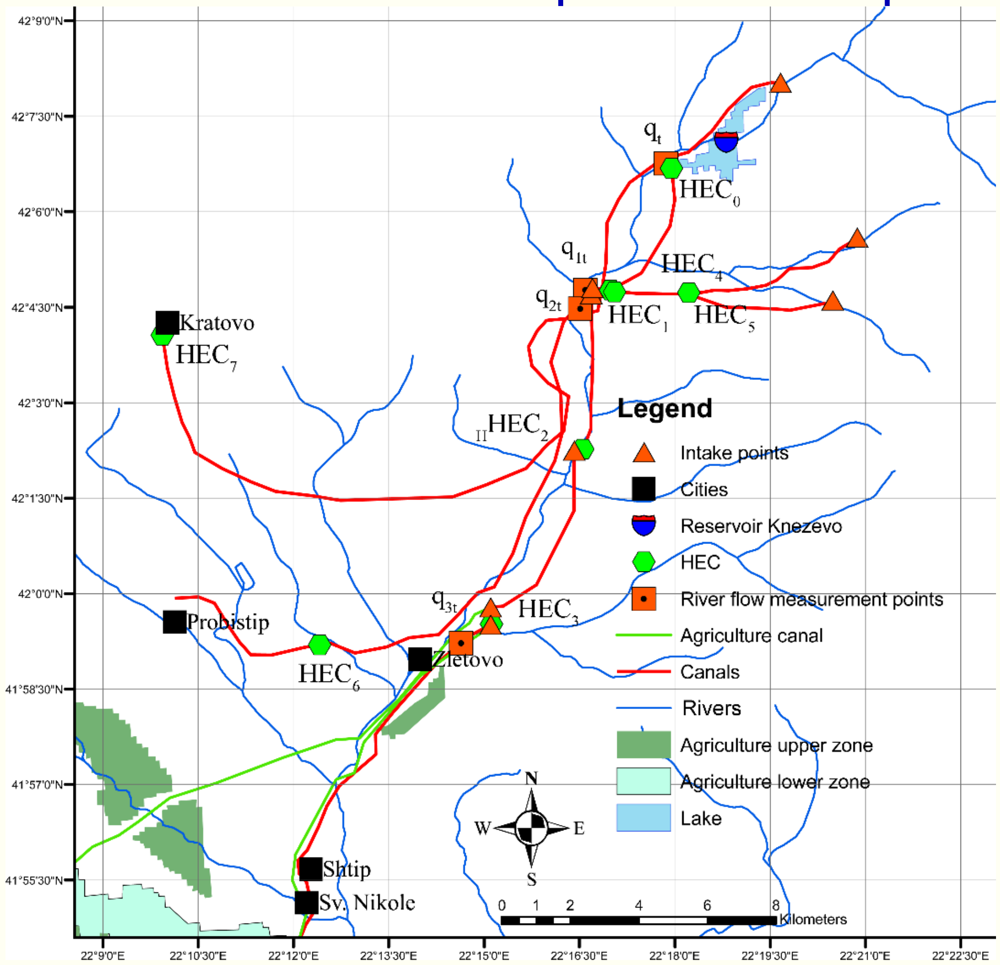
$$p_{q_{t+1}|q_t} = P\{\ \mathrm{q}_{\mathrm{t+1}} \text{ in interval } \mathrm{t+1} \mid \mathrm{q}_{\mathrm{t}} \text{ in interval } \mathrm{t}\ \}$$

and nRL (nested Reinforcement learning)

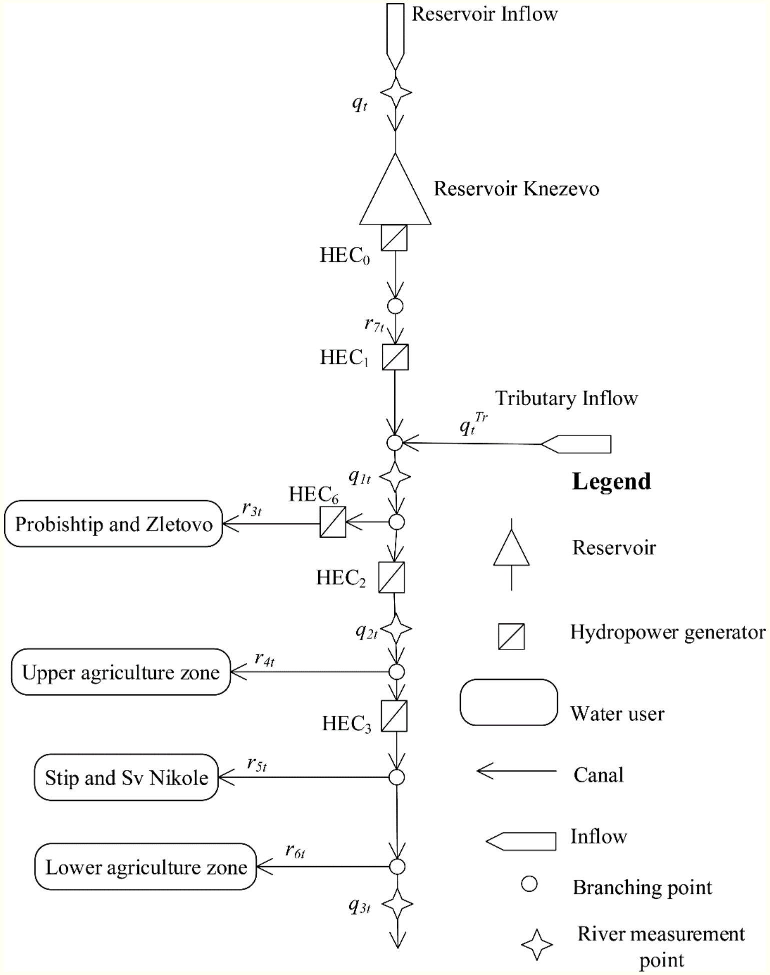


Zletovica river basin

Zletovica river basin is in the eastern part of the Republic of Macedonia.



Schematic representation of Zletovica river basin



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Objective function

The optimization problem has eight objectives and six decision variables.

weighted sum of squared deviations over the entire time horizon

$$g_t\left(s_t, s_{t+1}, a_t\right) = \sum_{i=1}^{8} w_{it} \cdot D_{it}^2$$

$$D_{1t} = \begin{cases} 0, & if \quad d_{1t} \geq h_t \\ h_t - d_{1t}, & if \quad d_{1t} < h_t \end{cases}$$

$$D_{2t} = \begin{cases} 0, & if \quad d_{2t} \leq h_t \\ d_{2t} - h_t, & if \quad d_{2t} > h_t \end{cases}$$

where d_{1t} and d_{2t} are the minimum and maximum level targets and h_t is the reservoir level height at time step t

Objective function

- Water demand users

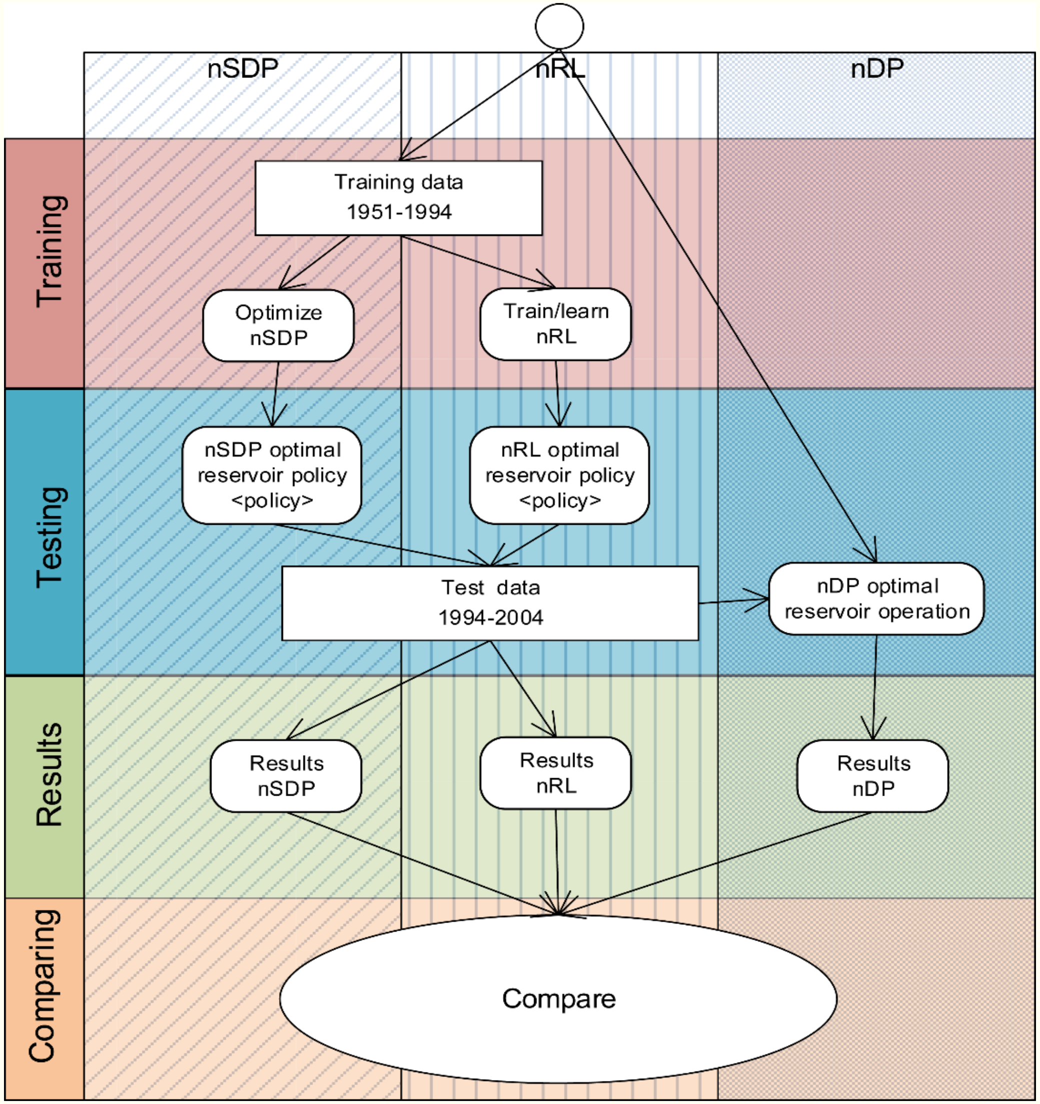
1) the towns of Zletovo and Probishtip (one intake), d_{3t},
2) the upper agricultural zone, d_{4t},
3) the towns of Shtip and Sveti Nikole (one intake), d_{5t},
4) the lower agricultural zone, d_{6t},
5) the minimum environmental flow, d_{7t}.

$$D_{it} = \begin{cases} 0, & if \quad d_{it} \le r_{it} \\ d_{it} - r_{it}, & if \quad d_{it} > r_{it} \end{cases}$$

where h_t is the hydropower demand and p_t is the hydropower production

$$D_{8t} = \begin{cases} 0, & if \quad \mathrm{d}_{8t} \le p_t \\ d_{8t} - p_t, & if \quad d_{8t} > p_t \end{cases}$$

Comparing optimal reservoir policies



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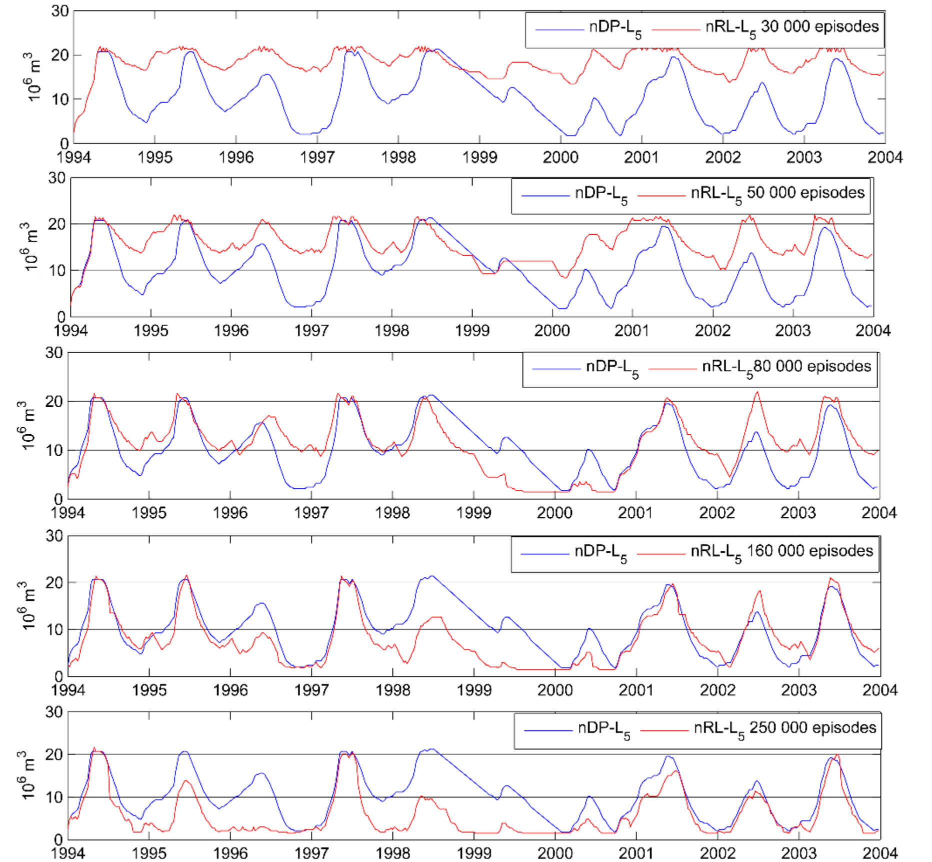
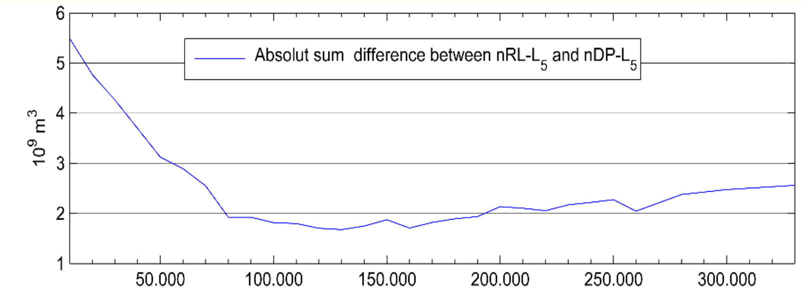
Results

- 55 years weekly data is separated in two parts 1) training and 2) testing. The data from 1951-1994 (2340 time-steps) is used for training and 1994-2004 (520 time-steps) for testing
- The reservoir operation volume 23 million m^3 is discretized in 73 equal levels (300 10^3 m^3 each).
- The minimum reservoir level target was set at 1021.5 [amsl],
- and the maximum reservoir level target at 1060 [amsl].
- The water supply, irrigation, and hydropower are set to their weekly demands
- The nDP is executed with 10 different sets of weights to provide screening of possible multi-objective solutions in the training data.
- The optimal reservoir policy has this structure <time step, storage volume, reservoir inflow, tributary inflow, next reservoir storage> ($<t, x_t, q_t, q_t^{Tr}, x_{t+1}>$)

weights	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8
nDP-L_5, nDP-Q_5 nSDP-L_5, nSDP-Q_5 nRL-L_5, nRL-Q_5	2,000,000	2,000,000	200	1	200	1	300	0.01

nRL agent learning

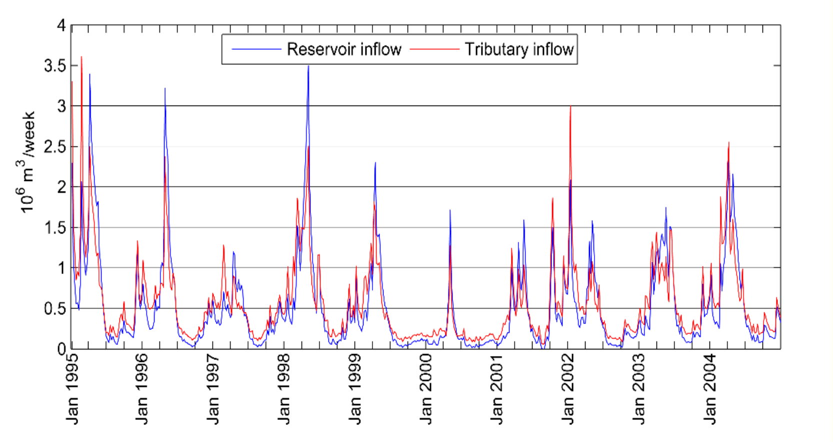


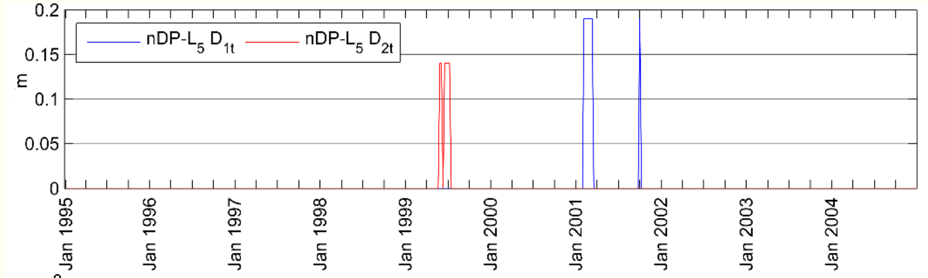


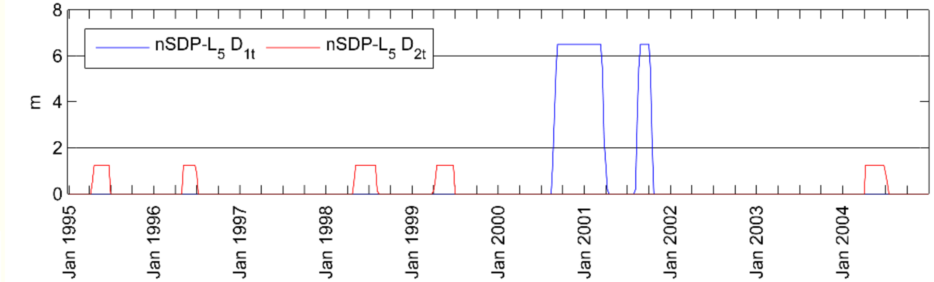
Sum of absolute difference between nRL-L5 and nDP-L5 measured as difference in reservoir volumes in period 1994-2004 as a function of the nRL number of episodes.

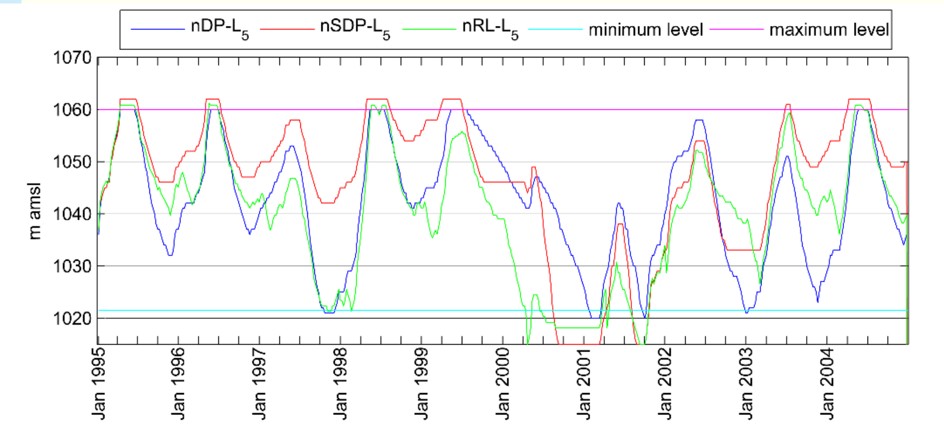
nRL-L5 agent learning with increasing the number of episodes: nDP-L5 target reservoir storage (blue) and nRL-L5 obtained reservoir storage (red) (testing period)

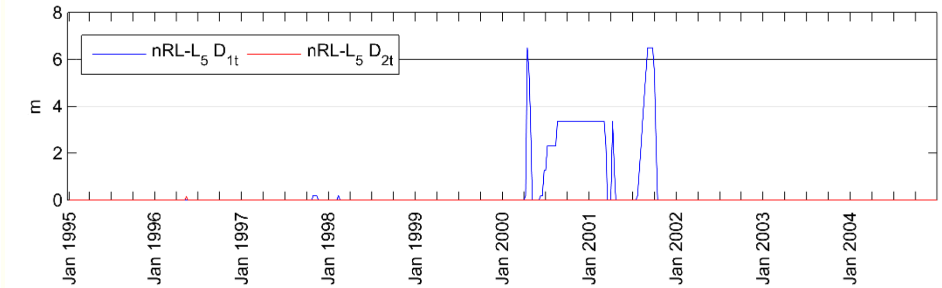
Results











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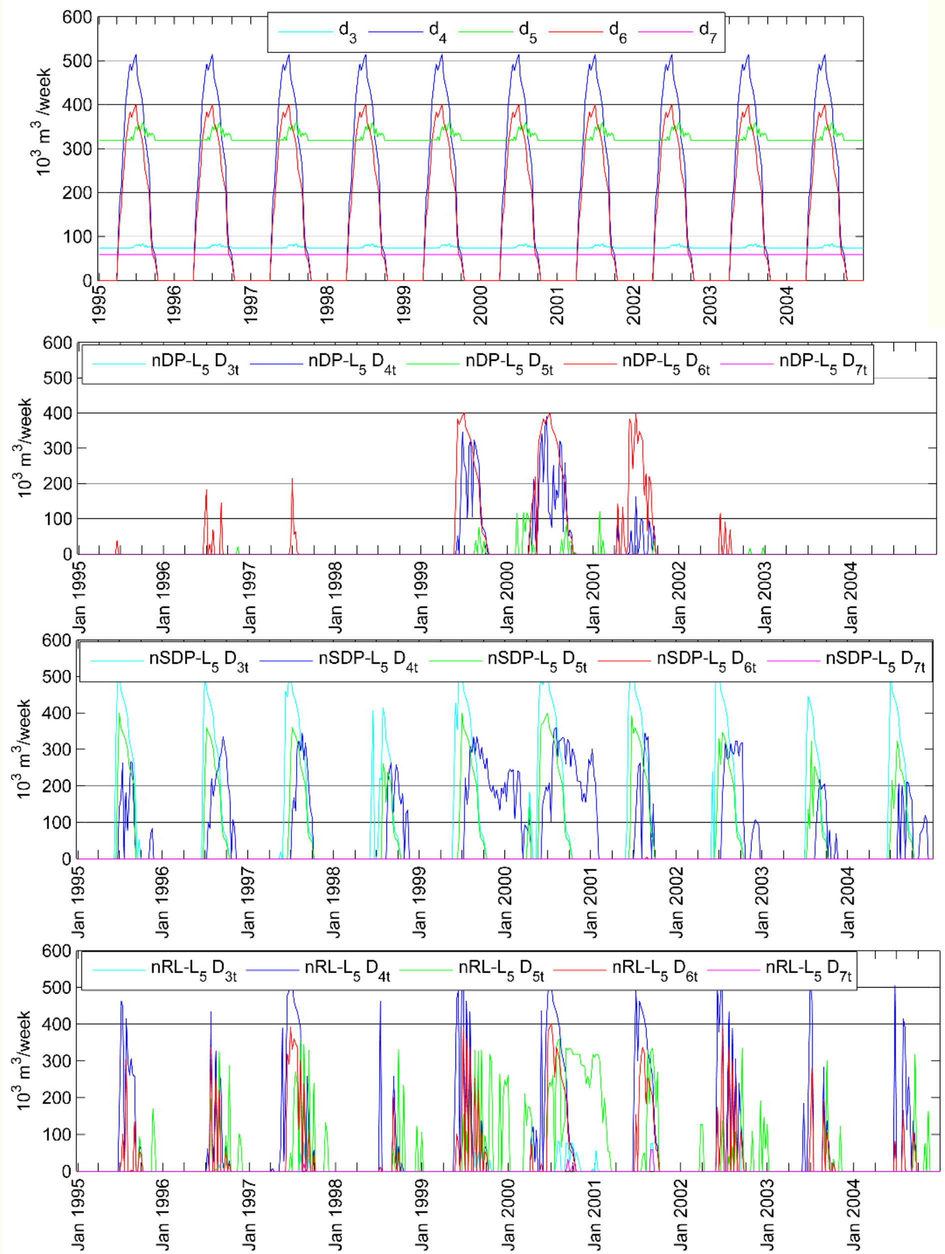
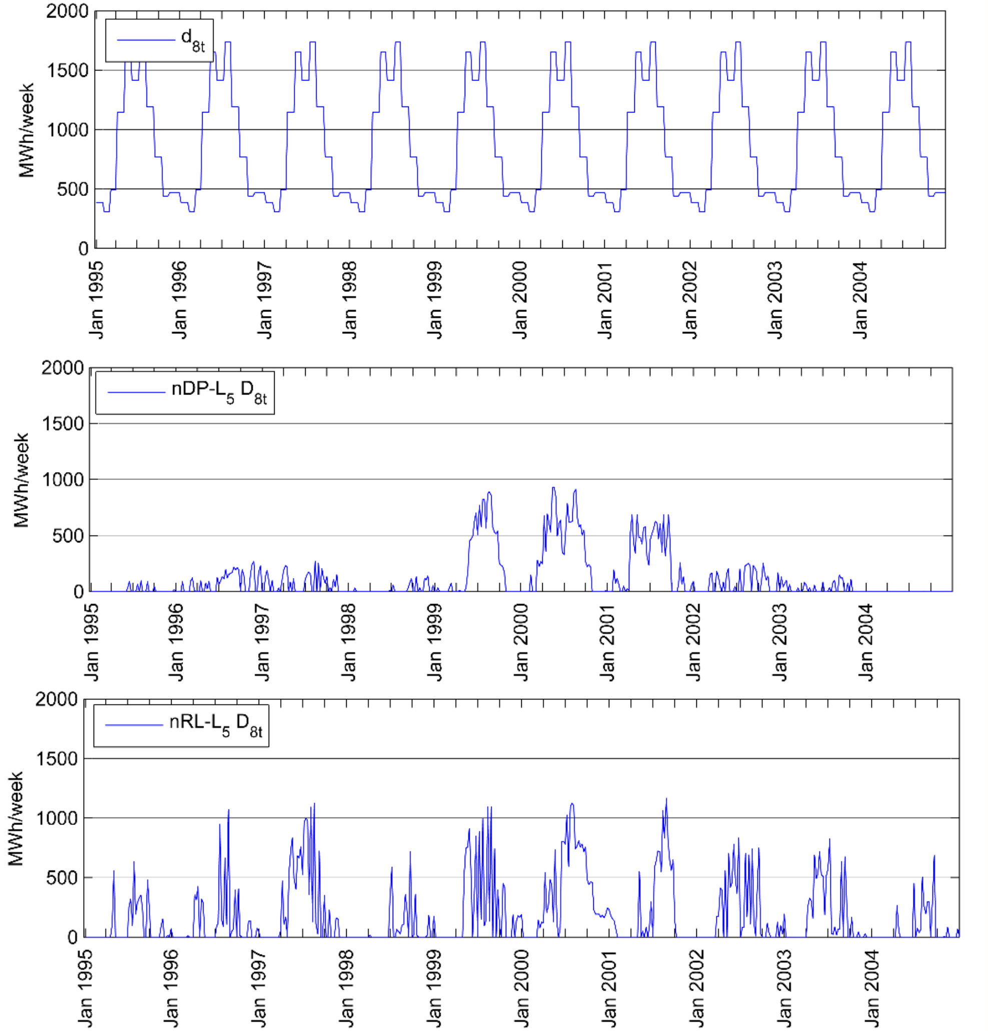
Results



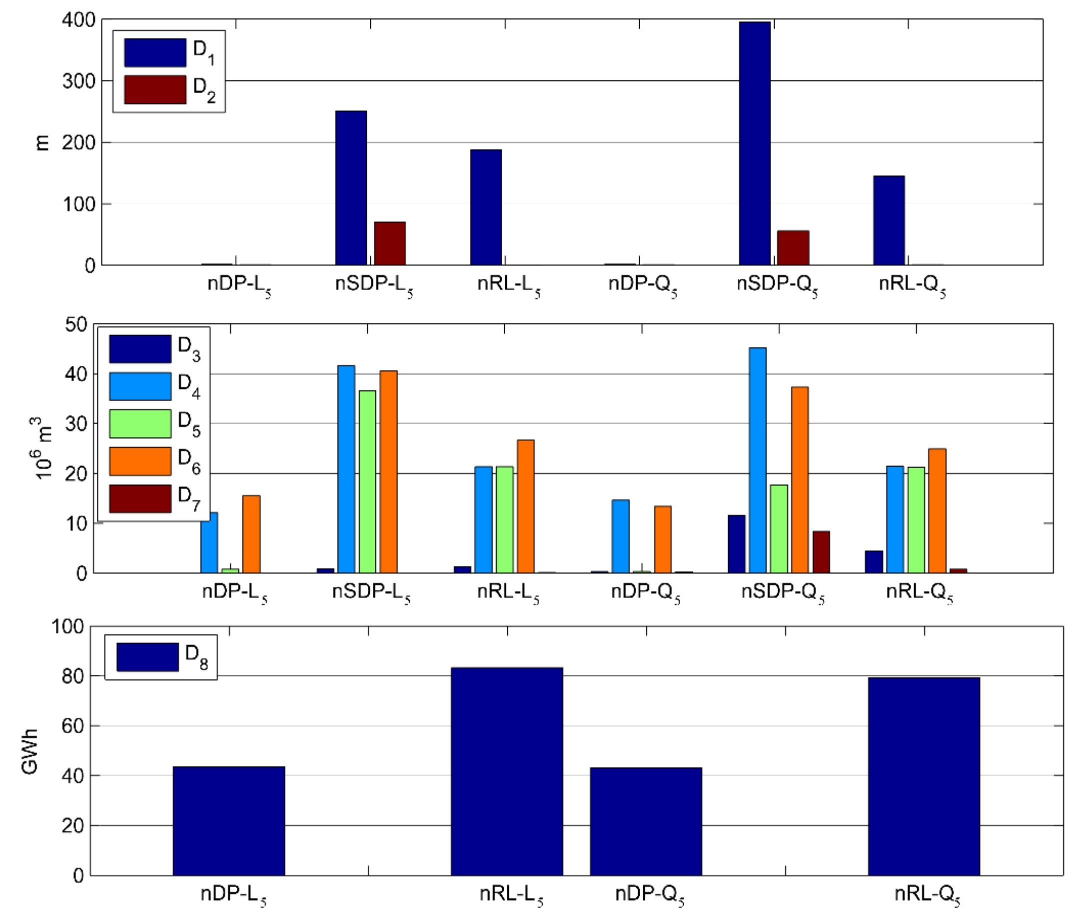
d3 d4 d5 d6 d7
10^3 m^3 /week
0 100 200 300 400 500 600
1995 1996 1997 1998 1999 2000 2001 2002 2003 2004
nDP-L5 D3t nDP-L5 D4t nDP-L5 D5t nDP-L5 D6t nDP-L5 D7t
10^3 m^3/week
Jan 1995 Jan 1996 Jan 1997 Jan 1998 Jan 1999 Jan 2000 Jan 2001 Jan 2002 Jan 2003 Jan 2004
nSDP-L5 D3t nSDP-L5 D4t nSDP-L5 D5t nSDP-L5 D6t nSDP-L5 D7t
10^3 m^3/week
Jan 1995 Jan 1996 Jan 1997 Jan 1998 Jan 1999 Jan 2000 Jan 2001 Jan 2002 Jan 2003 Jan 2004
nRL-L5 D3t nRL-L5 D4t nRL-L5 D5t nRL-L5 D6t nRL-L5 D7t
10^3 m^3/week
Jan 1995 Jan 1996 Jan 1997 Jan 1998 Jan 1999 Jan 2000 Jan 2001 Jan 2002 Jan 2003 Jan 2004

Results



2000
1500
1000
500
0
MWh/week
d8t
Jan 1995
Jan 1996
Jan 1997
Jan 1998
Jan 1999
Jan 2000
Jan 2001
Jan 2002
Jan 2003
Jan 2004
nDP-L5 D8t
nRL-L5 D8t

Results



Comparison of the sum of minimum level (D1) and maximum level (D2) deviations, sum of users' deficit (D3-7) and sum of hydropower deficit (D8) in the testing period 1994-2004

Conclusions

The nested algorithms have the following advantages:

- Effectively alleviate the curse of dimensionality in optimal reservoir operation.

(optimization problem has eight objectives and six decision variables)

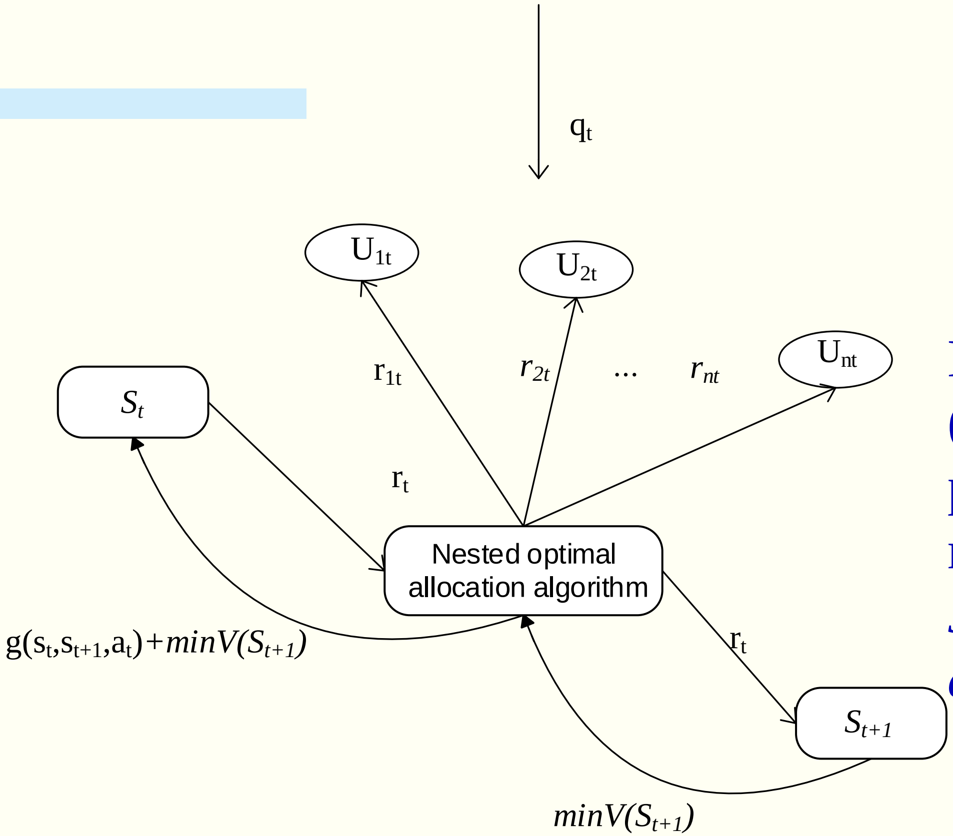
- They have better optimization capabilities compared to the DP aggregated water demand approach (and similar SDP and RL) and can solve problems that are more complex where the DP aggregated water demand approach is not feasible.
- Computationally, they are very efficient and runs fast on standard personal computers. The presented case study optimization was executed in less than five minutes.
- The algorithms allow for employing dense and variable discretization on the reservoir volume and release.
- Support using a variable weight at each time step for every objective function.

Conclusion

- Provides a framework for including many objectives in the nested optimization algorithm without a significant change in the source code or an increase in the computational expenses.
- Different optimization algorithms can be used in the nesting for water allocation, however, since nested optimization has to be repeated multiple times (for each transition of DP) the algorithm used for this purpose needs to be fast.
- The nSDP and nRL policies were benchmarked against the nDP results and it was obvious that the nRL performs better than nSDP overall and for all objectives separately. The main conclusion is that nRL is a better and more capable optimal reservoir algorithm than nSDP, at least in this case study.

The main idea is to include nested optimization algorithm inside the state transition, which lowers the problem dimension. With this method, it is possible to solve optimization problems that are currently unsolvable with classical methods, rapidly decrease the optimization time and improve the result that was demonstrated in this paper.

Thank you



Delipetrev, B., Jonoski A., Solomatine D. (2015) "A novel nested dynamic programming (nDP) algorithm for multipurpose reservoir optimization" *Journal of Hydroinformatics. doi:10.2166/hydro.2015.066*

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