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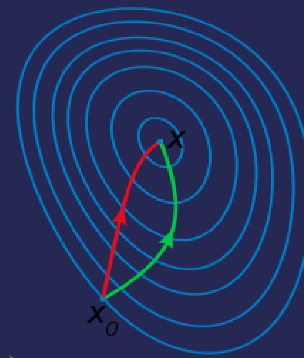

Real-Time Reservoir Operation by Tree-Based Model Predictive Control Including Forecast Uncertainty

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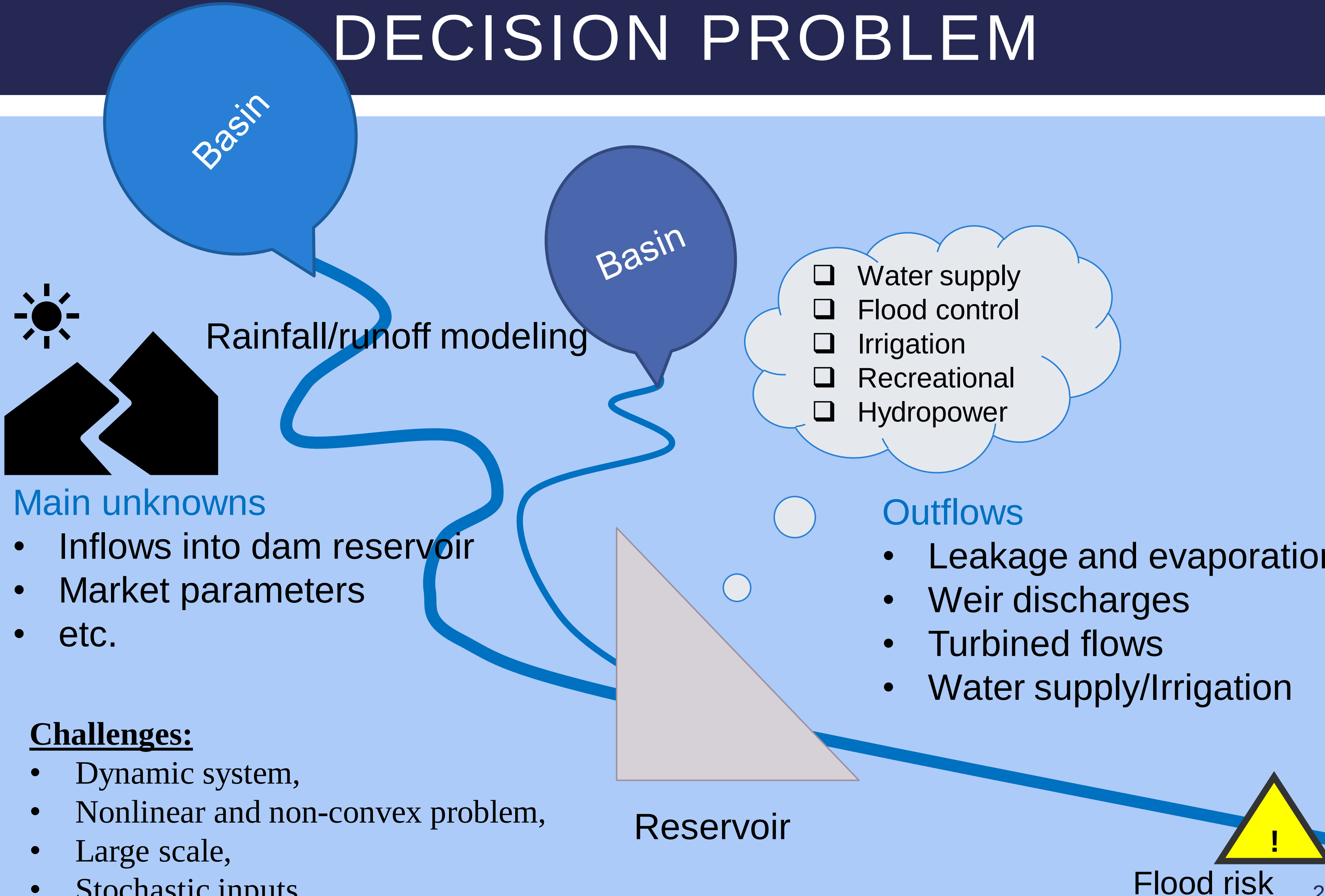
REAL-TIME RESERVOIR SYSTEM DECISION PROBLEM



Main unknowns

- Inflows into dam reservoir
- Market parameters
- etc.

Outflows

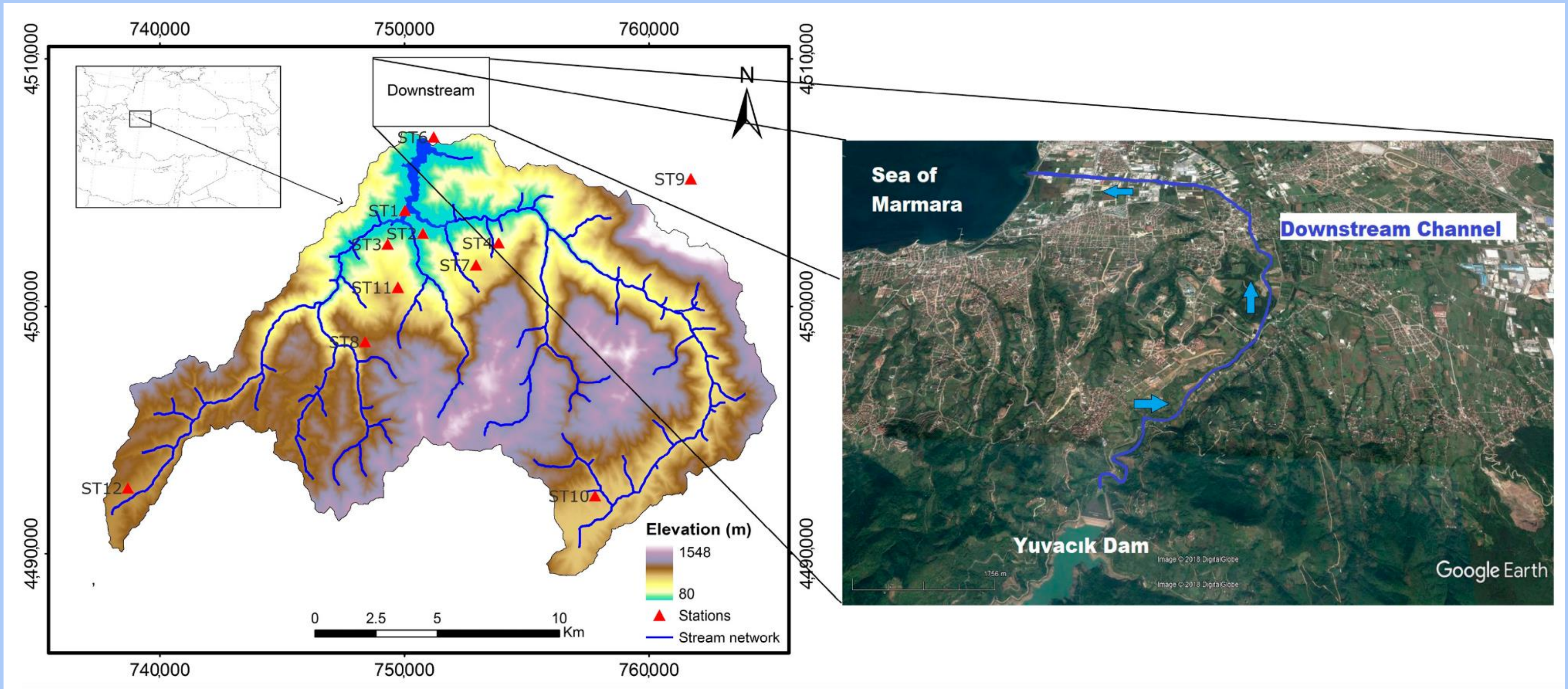
- Leakage and evaporation
- Weir discharges
- Turbined flows
- Water supply/Irrigation

Challenges:

- Dynamic system,
- Nonlinear and non-convex problem,
- Large scale,
- Stochastic inputs

STUDY AREA: YUVACIK DAM & BASIN

Uncertainty becomes much larger when managing small basins and small rivers.



- ➢**11 Rain gauges**
- ➢**6 Temp. sensors**
- ➢**5 Snow depth sensors**

Main Tasks: Water supply (1.5 m populated Kocaeli) + Flood control (City)

DANGER OF FLOODING

- Excess amount of water during March through May months due to relatively small capacity is being spilled to a 12 km long manmade downstream channel and flowed into Marmara Sea.
- This channel passes through a rural and an industrial district and therefore, spillway discharges are getting important.
- These two photos are taken on 2010 year. Although spillway gates were not operated, a flood was observed in downstream channel area.

THE BACKGROUND OF THE CURRENT STUDY CAN BE FOUND AT…

Gökçen Uysal[1,2] · Dirk Schwanenberg[1,3] · Rodolfo Alvarado-Montero[1] · Aynur Şensoy[2]

Received: 28 November 2016 / Accepted: 2 October 2017

Abstract Reservoir operations require enhanced operating procedures for water systems under stress attributed to growing water demand and consequences of changing hydro-climatic conditions. This study focuses on the management of the Yuvacik Dam Reservoir for water supply and flood mitigation in the Marmara Region of Turkey. We present an improved operating technique for fulfilling the conflicting water supply and flood mitigation objectives. This is accomplished by incorporating the long term water supply objectives into a Guide Curve (GC) whereas the extreme floods are attenuated by means of short-term optimization based on Model Predictive Control (MPC). The reference case implements operating rules with a constant GC at maximum forebay elevation targeting the fulfillment of the water supply objective. We compare the reference with a new time-dependent GC, derived using an Implicit Stochastic Optimization (ISO) approach. This new curve shows nearly the same performance regarding the water supply objectives, but significantly reduces the flooding risk downstream of the dam. Possible flood events observed at the end of the wet season, when the reservoir is at the maximum level to enable water supply for the dry season, can be eliminated by the application of an additional short-term optimization by MPC. The robustness of the approach is demonstrated via hindcasting experiments.

Keywords Reservoir operation · Optimization · Simulation · Water supply · Flood mitigation · Model Predictive Control

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s11269-017-1828-x) contains supplementary material, which is available to authorized users.

✉ Gökçen Uysal
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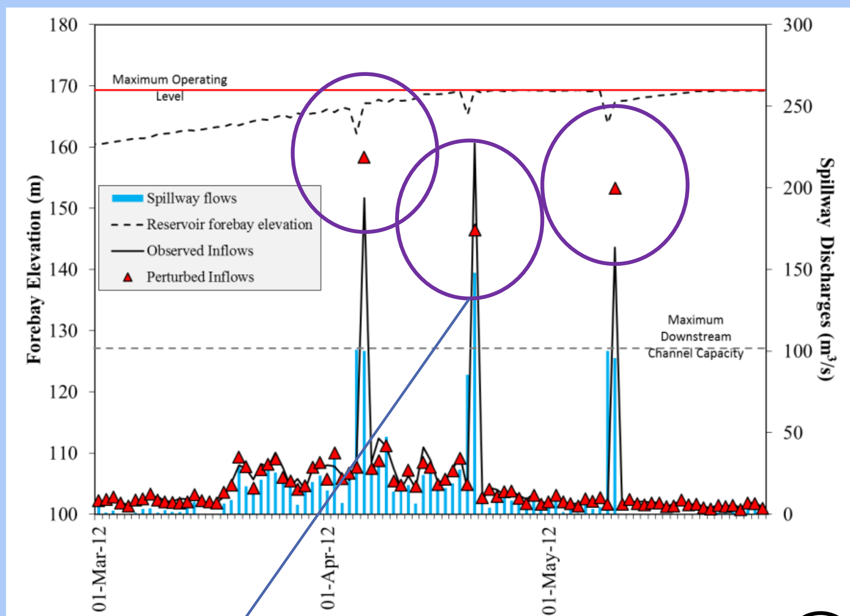
- **Uysal et al. (2018a)** aims to derive operating Guide Curve (GC) based on Model Predictive Control (MPC) application.
- Also, the closed-loop simulation (hindcasts) shows the advantages of using MPC.

Uysal et al. (2018a)

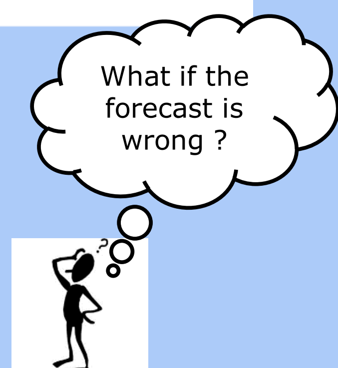
THE MAIN CONCEPT WAS…



Uysal et al. (2018a)

- ✓ Proactive operation!

BUT



- While (daily) variable GC is useful for long term strategies in decision making, the model is not robust aganist forecast uncertainty.

AIM & CONTENT OF THIS STUDY

- This study practices (hourly) ensemble streamflows as input of the recurrent reservoir operation problem which can incorporate:

UNCERTAIN
TY

(i) forecast uncertainty,

(ii) forecasts with a higher lead-time and

(iii) a higher stability

Thus, the aim of this study is to set a TB-MPC based real-time reservoir operation via hindcasting experiments.

FOR MORE INFORMATION...

water

MDPI

Article

Real-Time Flood Control by Tree-Based Model Predictive Control Including Forecast Uncertainty: A Case Study Reservoir in Turkey

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Abstract: Optimal control of reservoirs is a challenging task due to conflicting objectives, complex system structure, and uncertainties in the system. Real time control decisions suffer from streamflow forecast uncertainty. This study aims to use Probabilistic Streamflow Forecasts (PSFs) having a lead-time up to 48 h as input for the recurrent reservoir operation problem. A related technique for decision making is multi-stage stochastic optimization using scenario trees, referred to as Tree-based Model Predictive Control (TB-MPC). Deterministic Streamflow Forecasts (DSFs) are provided by applying random perturbations on perfect data. PSFs are synthetically generated from DSFs by a new approach which explicitly presents dynamic uncertainty evolution. We assessed different variables in the generation of stochasticity and compared the results using different scenarios. The developed

HINDCAST EXPERIMENTS

- **Hindcasting experiments*** are *the representation of a real-time system* by an iterative process.
- We apply closed-loop hindcasting experiments by the following three modes:

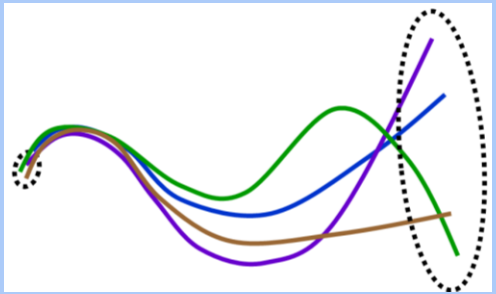
1. *Perfect Hindcast Experiments*: Best! (No Uncertainty)
2. *Deterministic Hindcast Experiments*: No uncertainty (Only one single forecast member)
3. Probabilistic Hindcast Experiments: Multiple forecast members! This represents the skill of ensemble PSF evaluation by multi-stage stochastic TB-MPC.

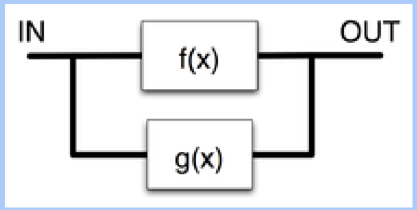
* Check Uysal et al. (2018b) for details.

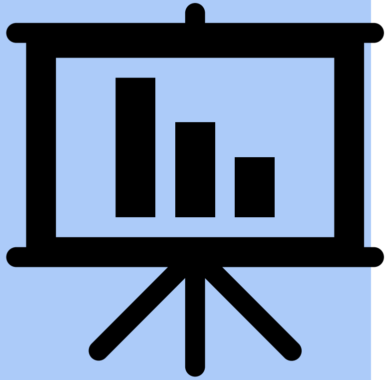
METHODOLOGY

… is comprised of …

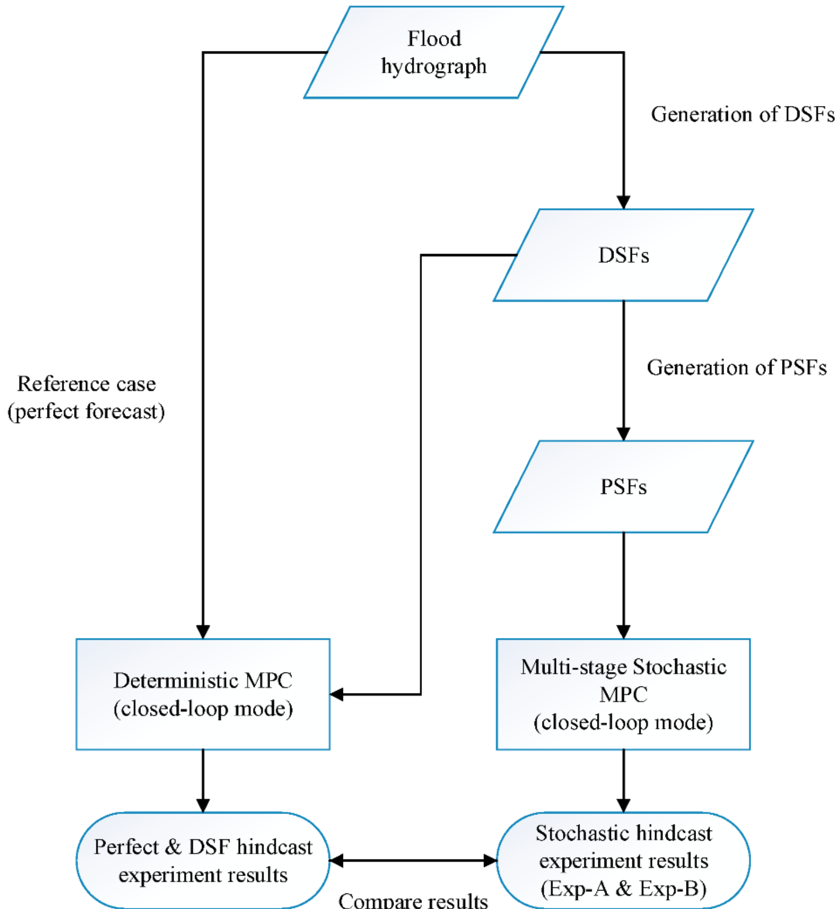
1. **Reservoir Controls**
2. **Optimization**
3. **Uncertainties in flow forecasting**
4. **Stochastic Optimization + Control = ?**







This study complements deterministic methods by PSF integrated TB-MPC including forecast uncertainty.



Main Flow Chart

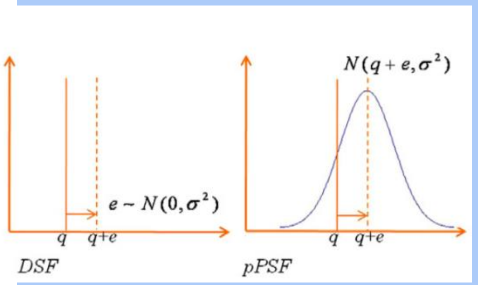
- Mainly three scenarios are conducted in MPC
  1. Perfect MPC (using observed data, Q_{100} flood hydrograph)
  2. Deterministic MPC (using DSFs)
  3. Multi-stage MPC (using PSFs)

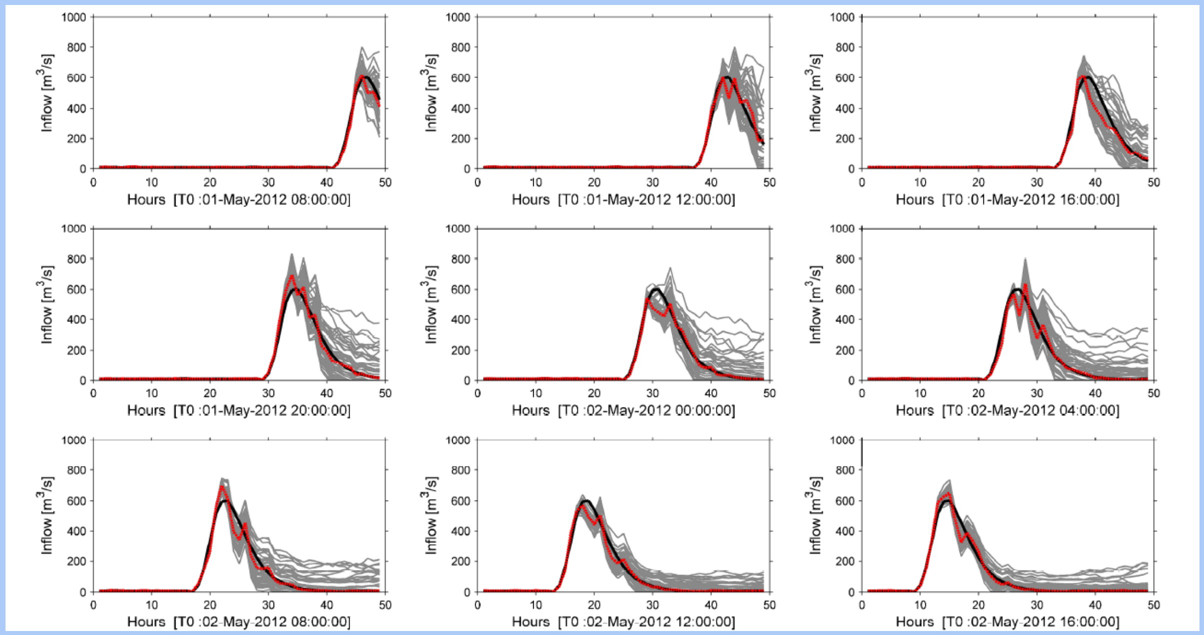
Deterministic Streamflow Forecasts (DSFs) are provided by applying random perturbations on perfect data.

Uysal et al. (2018b)

FORECAST GENERATION (PERFECT, DSF & PSF)

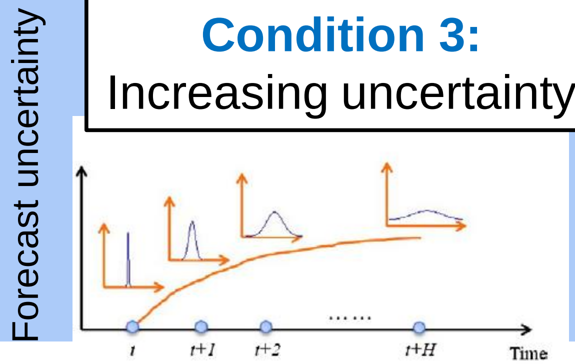
Condition 1:
Normal distribution





Condition 2:
Correlation between forecasts

Condition 3:
Increasing uncertainty



Condition 4:
Updating the inflows (depending on condition)

Uysal et al. (2018b)

MODEL PREDICTIVE CONTROL (MPC)

Simultaneous MPC

$$x^k = f(x^{k-1}, x^k, u^k, d^k)$$

$$y^k = g(x^k, u^k, d^k)$$

where x, y, u, d are respectively the state, dependent variable, control and disturbance vectors, and $f()$, $g()$ are functions representing an arbitrary linear or nonlinear water resources model.

Cost function:

$$\min_{u, x \in \{0, \ldots, T\}} \sum_{k=1}^{N-1} J(x^k, u^k, d^k) + E(x^N, u^N, d^N)$$

Subject to:

$$h(x^k, y^k, u^k, d^k) \leq 0, k = 1, \ldots, N$$

$$x^k - f(x^k, x^k, u^k, d^k) = 0$$

the related model (herein, reservoir simulation equations) becomes an equality constraint of the optimization problem in the last equation.

...enabling the use of state-of-the-art Nonlinear Programming such as the open source optimizer IPOPT (**Wächter and Biegler 2006**). The model itself is implemented in RTC-Tools (Schwanenberg et al. 2014).

MULTI-STAGE STOCHASTIC SET-UP

The problem is extended through multi-stage stochastic set-up by changing d^k with d_j^k where j denotes the ensemble index $(j = 1, \ldots, M)$ and k denotes the time instant $(k = 1, \ldots, N)$.

$$\min_{u, x \in \{0, \ldots, T\}} \sum_{j=1}^{M} p_j \sum_{k=1}^{N-1} J(x_j^k, u_j^k, d_j^k) + E(x_j^N, u_j^N, d_j^N) \tag{6}$$

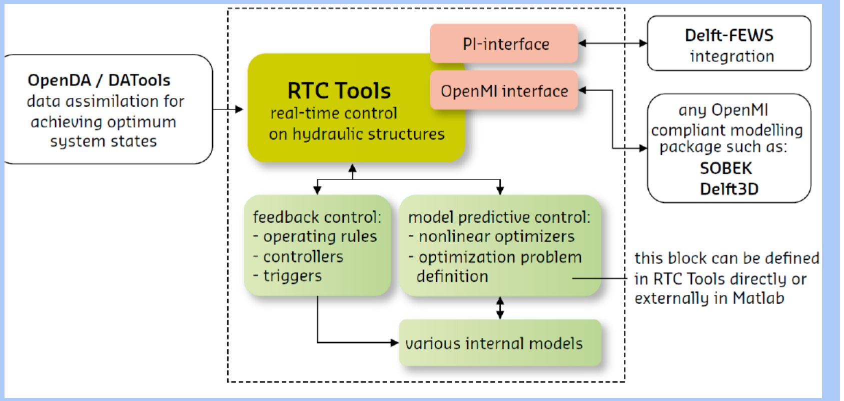
where p_j stands for the probability of the ensemble member, M stands for the number of the ensembles.

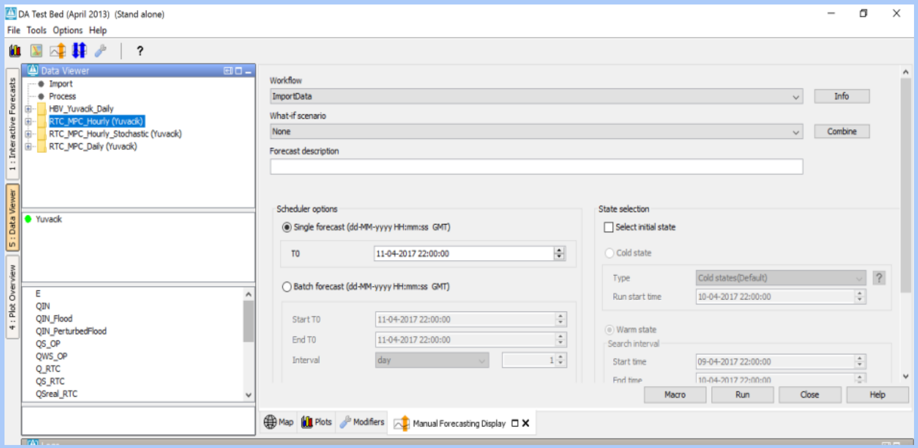
Definition of control variable u_j^k identifies the approach for stochastic MPC set-up. At this point, multi-stage stochastic optimization (so called Tree-based MPC, TB-MPC) is dedicated way which uses scenario trees for disturbance, states and control trajectories [4].

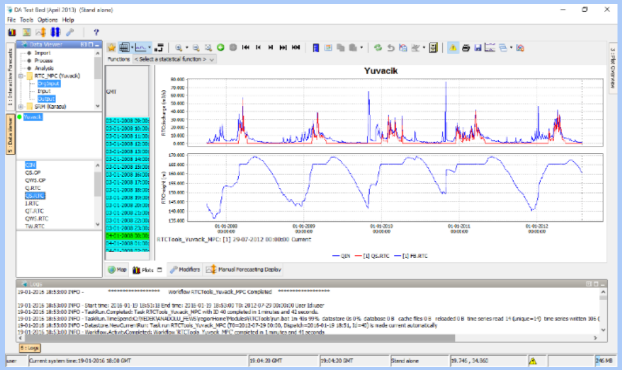
Uysal et al. (2018b)

CONTROL INTERFACE AND MODELING SOFTWARE

- Deltares-Flood Early Warning System (FEWS) (Werner vd., 2013)
- Real Time Control (RTC)-Tools (Schwanenberg ve Becker, 2009)

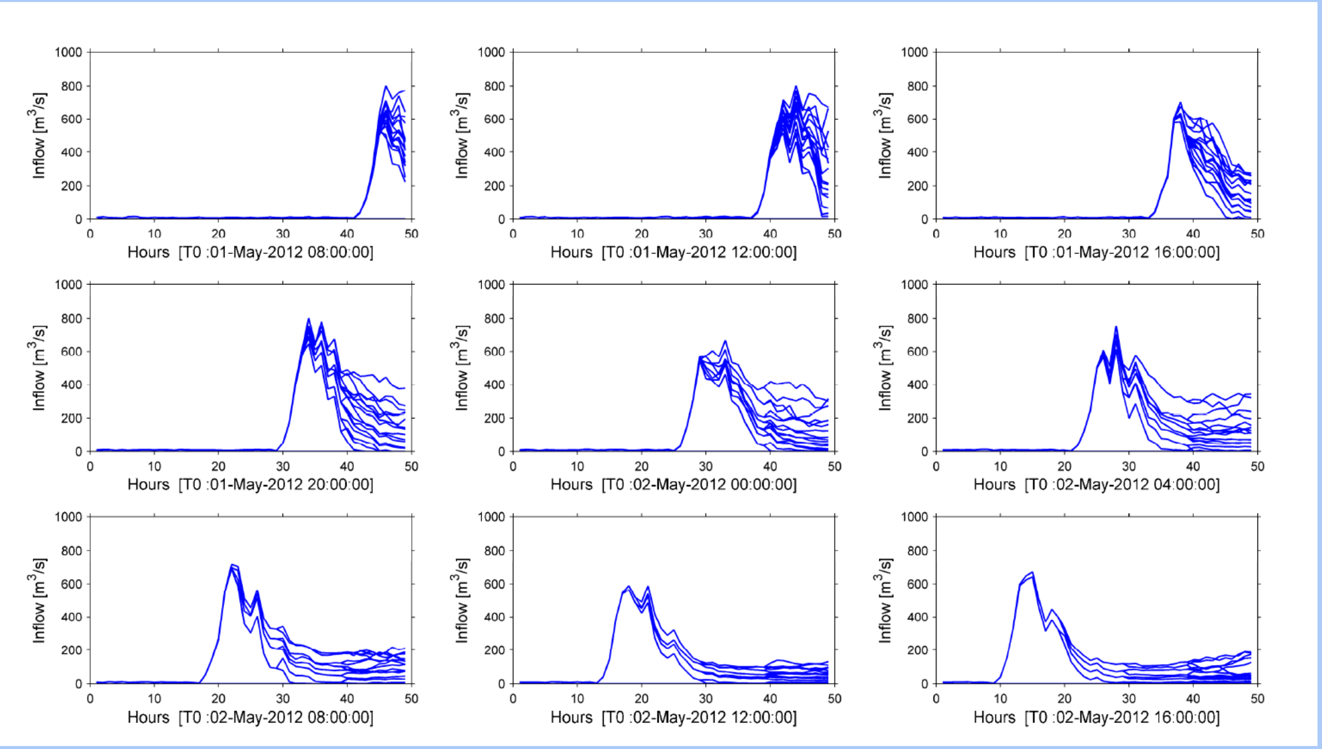






TREE REDUCTION METHOD

- Tree-based reduction method is applied to ensemble members Fan et al. (2016)



PSF ensemble members (50) transformed into optmization trees (16 branches)

Uysal et al. (2018b)

MODEL SET-UP

Storage equation

$$s^k = s^{k-1} + \Delta t\left(Q_I^k - Q_S^k - Q_{WS}^k\right)$$

piecewise-linear level-storage relation

$$fb^k = f_{ls}\left(s^k\right)$$

$$r^k = s^k - s^{k-1} - \Delta t\left(Q_I^k - Q_S^k - Q_{WS}^k\right) = 0$$

mass balance definition

$$fb_{min} \leq fb^k \leq fb_{max}$$

The system's physical limits

$$Qs_{min} \leq Qs^k \leq Qs^k_{max}$$

$$Qs^k_{max} = f_{sdc}\left(fb^k\right)$$

A reservoir having a limited capacity should include the terms below for hourly management:

$$J1(fb) = w_1 \sum_{k=1}^{N}\left(f_{max} - fb^k\right)$$

$$J2(Qs) = w_2 \sum_{k=1}^{N}\left(Qs^k\right)$$

$$J3(Qs) = w_3 \sum_{k=1}^{N} \max\left(Qs^k - Q_{set}, 0\right)^2$$

GC issue

$$J4(fb) = w_4 \sum_{k=1}^{N} \max\left(fb^k - fb_{set}, 0\right)^2$$

$$J5(Qs) = w_5 \sum_{k=1}^{N}\left(Qs^{k+1} - Qs^k\right)^2$$

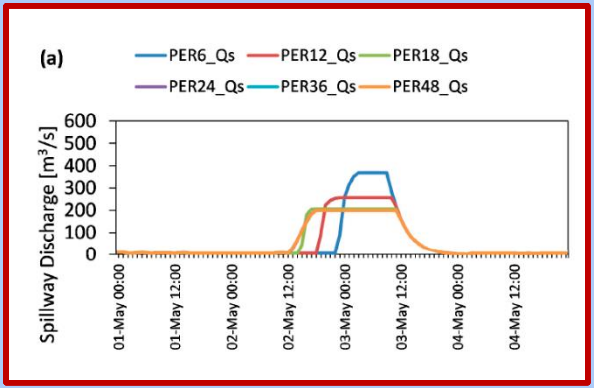
Objective Function

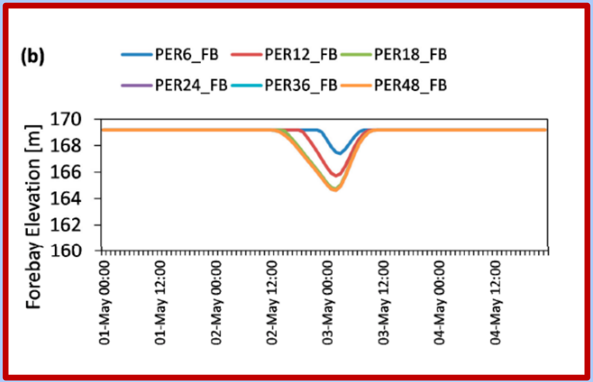
$$\min_{k \in \{0,\ldots,T\}} J(fb, Qs) = J1 + J2 + J3 + J4 + J5$$

Uysal et al. (2018b)

RESULTS (PERFECT AND DETERMINISTIC HINDCASTS)

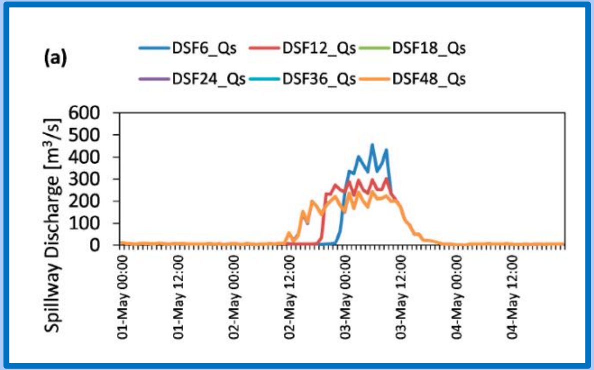
- If there is no uncertainty in forecasts

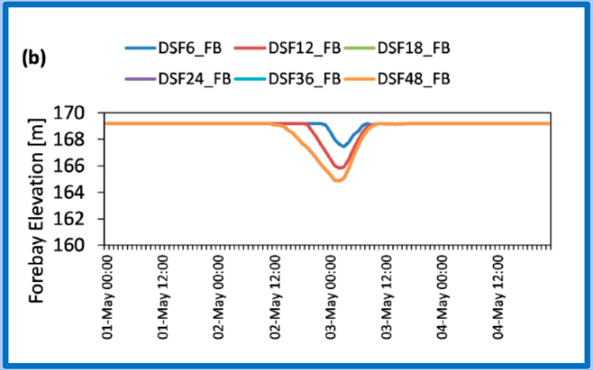




Forecast horizon should be at least 18 hr

- However, forecasts are biased and single forecast based results does not satisfy targets (>200 cms = flooding!)

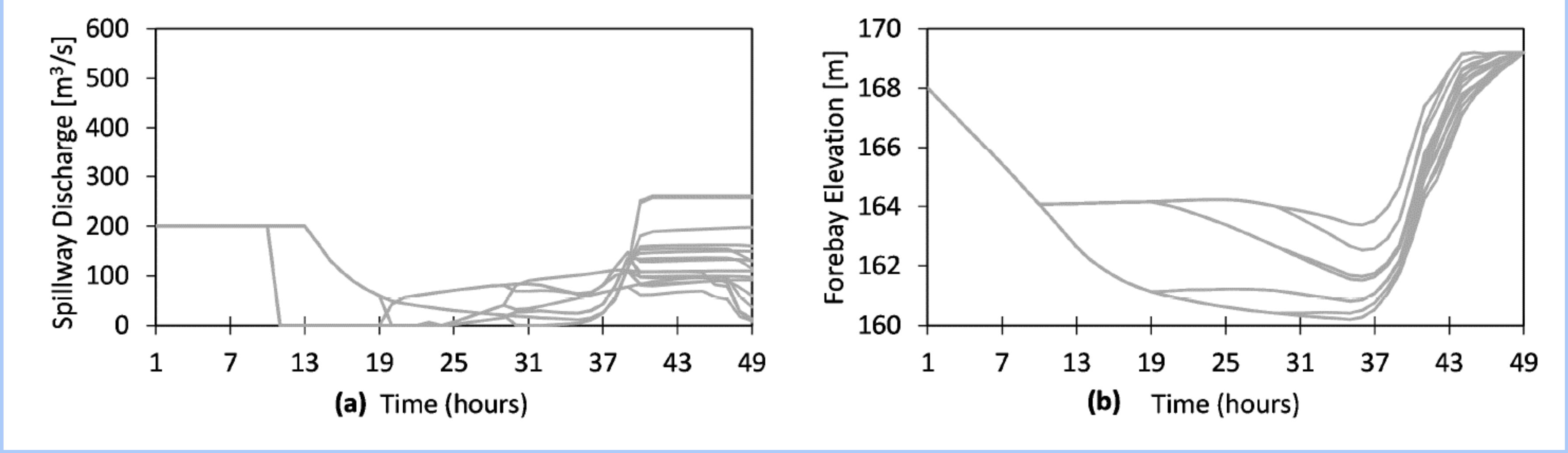




Uysal et al. (2018b)

AN OPEN-LOOP EXAMPLE RESULT FOR STOCHASTIC OPTMIZATION

- Open-loop optimization results of multi-stage stochastic optimization (from Sce-Q100a) for 48 hr ahead



(a) Spillway discharge trees (m^3/s);
(b) (b) forebay elevation trees (m).

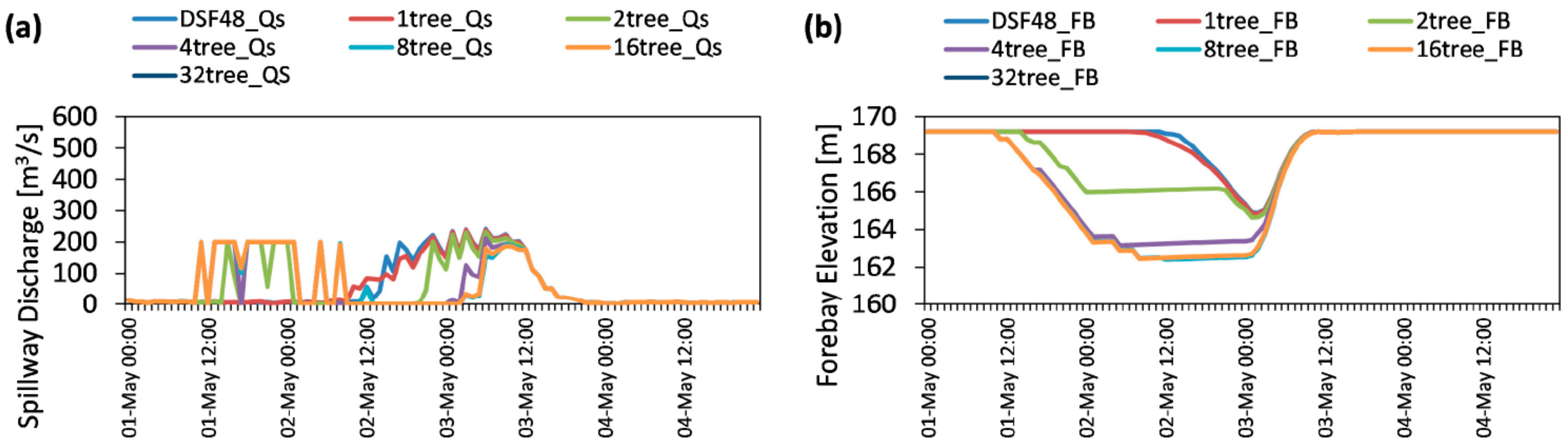
Uysal et al. (2018b)

RESULTS (DIFFERENT BRANCHES)

What is should be the optimum branch number (due to reduction method)?

- Optimum results are received after 16 tree branches

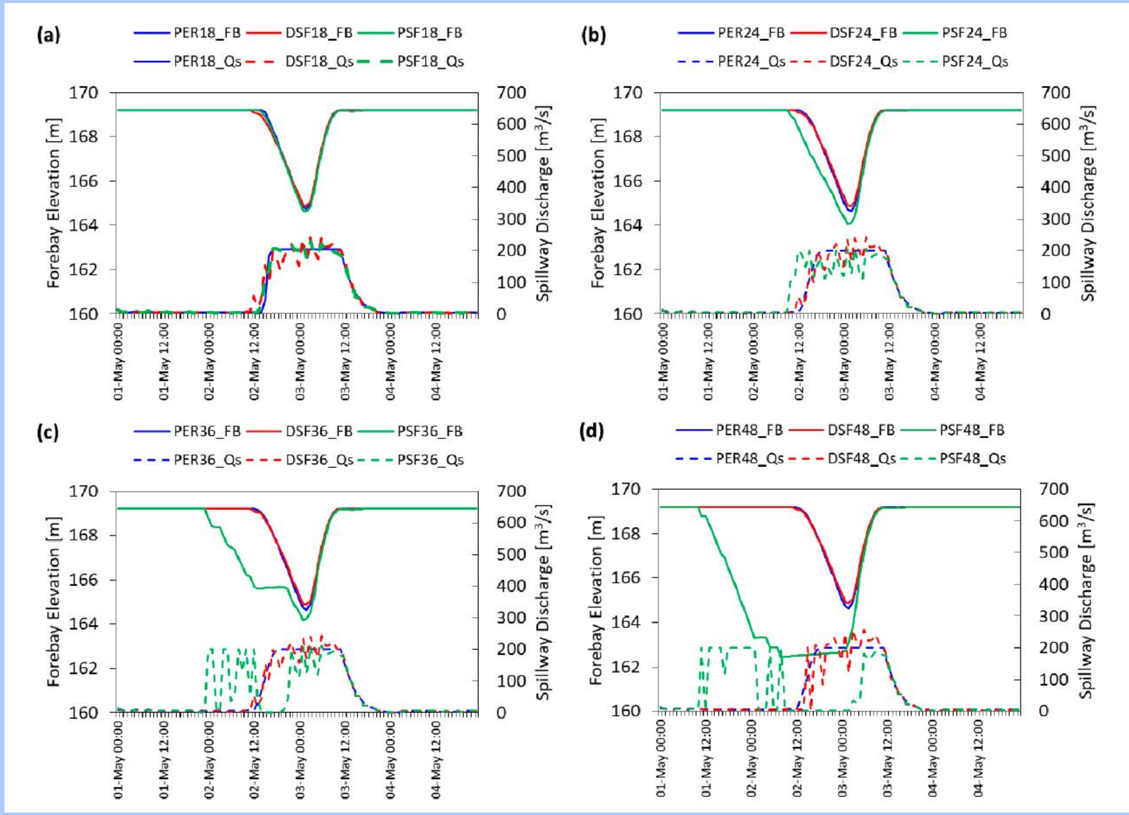
Note: 1 tree stochastic MPC = Deterministic MPC (almost)



Comparison of closed-loop MPC with different tree reduction branches for 48 h forecast horizon (Sce-Q100a): (a) Spillway discharge (m3/s); (b) forebay elevation (m).

RESULTS (FOREBAY ELEVATION & SPILLWAY DISCHARGE)

Comparison of deterministic (perfect and DSF) and stochastic (PSF) closed-loop MPC results with different forecast horizons (Sce-Q100a): (a) 18 h; (b) 24 h; (c) 36 h;



Uysal et al. (2018b)

Additional scenarios are also tested in Uysal et al. (2018b)

COMPARISON WITH DIFFERENT METRICS (1)

Peakflow assessment of deterministic and stochastic closed-loop MPC results for different inflow conditions with forecast horizons of 48 h.

Flood Hydrograph	Scenarios	Peakflow at Yuvacik Outlet (m^3/s)	
		Deterministic MPC	Stochastic MPC
Q_{25}	Sce-Q25a	243	231
	Sce-Q25b	255	243
	Sce-Q25c	248	243
Q_{50}	Sce-Q50a	241	211
	Sce-Q50b	245	200
	Sce-Q50c	246	200
Q_{100}	Sce-Q100a	242	200
	Sce-Q100b	269	235
	Sce-Q100c	278	233

Flood volume assessment of deterministic and stochastic closed-loop MPC results for different inflow conditions with forecast horizon of 48 h.

Flood Condition	Scenarios	Total Flood Volume (1×10^6 m^3)	
		Deterministic MPC	Stochastic MPC
Q_{25}	Sce-Q25a	0.507	0.302
	Sce-Q25b	0.549	0.254
	Sce-Q25c	0.438	0.271
Q_{50}	Sce-Q50a	0.666	0.062
	Sce-Q50b	0.471	0.004
	Sce-Q50c	0.331	0.004
Q_{100}	Sce-Q100a	0.690	0.004
	Sce-Q100b	1.256	0.184
	Sce-Q100c	1.018	0.127

Uysal et al. (2018b)

COMPARISON WITH DIFFERENT METRICS (2)

FSI value assessment of deterministic and stochastic closed-loop MPC according to Flood Control Levels (FCLs) for different inflow conditions with forecast horizon of 48 h.

Flood Condition	Scenarios	Flood Storage Index (FSI)	
		Deterministic MPC	Stochastic MPC
Q_{25}	Sce-Q25a	0.652	0.800
	Sce-Q25b	0.659	0.990
	Sce-Q25c	0.659	0.796
Q_{50}	Sce-Q50a	0.566	0.723
	Sce-Q50b	0.598	0.770
	Sce-Q50c	0.606	0.758
Q_{100}	Sce-Q100a	0.457	0.650
	Sce-Q100b	0.463	0.645
	Sce-Q100c	0.456	0.645

$$FSI = \frac{\sum_{k=1}^{N} \boxed{v_f^k}}{\sum_{k=1}^{N} \boxed{v_{FCL}^k}}$$

effective flood storage

storage corresponds to flood control level

$$v_f^k = \begin{cases} \boxed{v_{act}^k} \; if \; \boxed{v^k} \le v_{FCL}^k \\ v_{FCL}^k \; if \; v^k > v_{FCL}^k \end{cases} \quad for \; \boxed{k} = 1, 2, \ldots N$$

actual volume of the flood control pool

current storage

time instant

Uysal et al. (2018b)

CONCLUSIONS

- Assessment of forecast uncertainty is still lack in real time operation of water resources optimization.
- *The operation of multi-purpose dam reservoir* having water supply, flood control targets is tested in a real-time operation against a major flood scenario.
- MPC models are developed to mimic a real-time control via hindcast experiments.
- Synthetic deterministic and probabilistic hourly streamflows with 48 hours lead-time are employed in deterministic and stochastic MPC models, respectively.
- Tree-based MPC is selected ***because of including forecast uncertainty consideration*** in the decision system.
- The preliminary results of TB-MPC are promising in terms of downstream region safety compared to deterministic MPC without harming water supply targets.
- In the future studies, the developed framework can be tested with numerical weather prediction based forecasts.

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