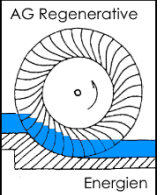




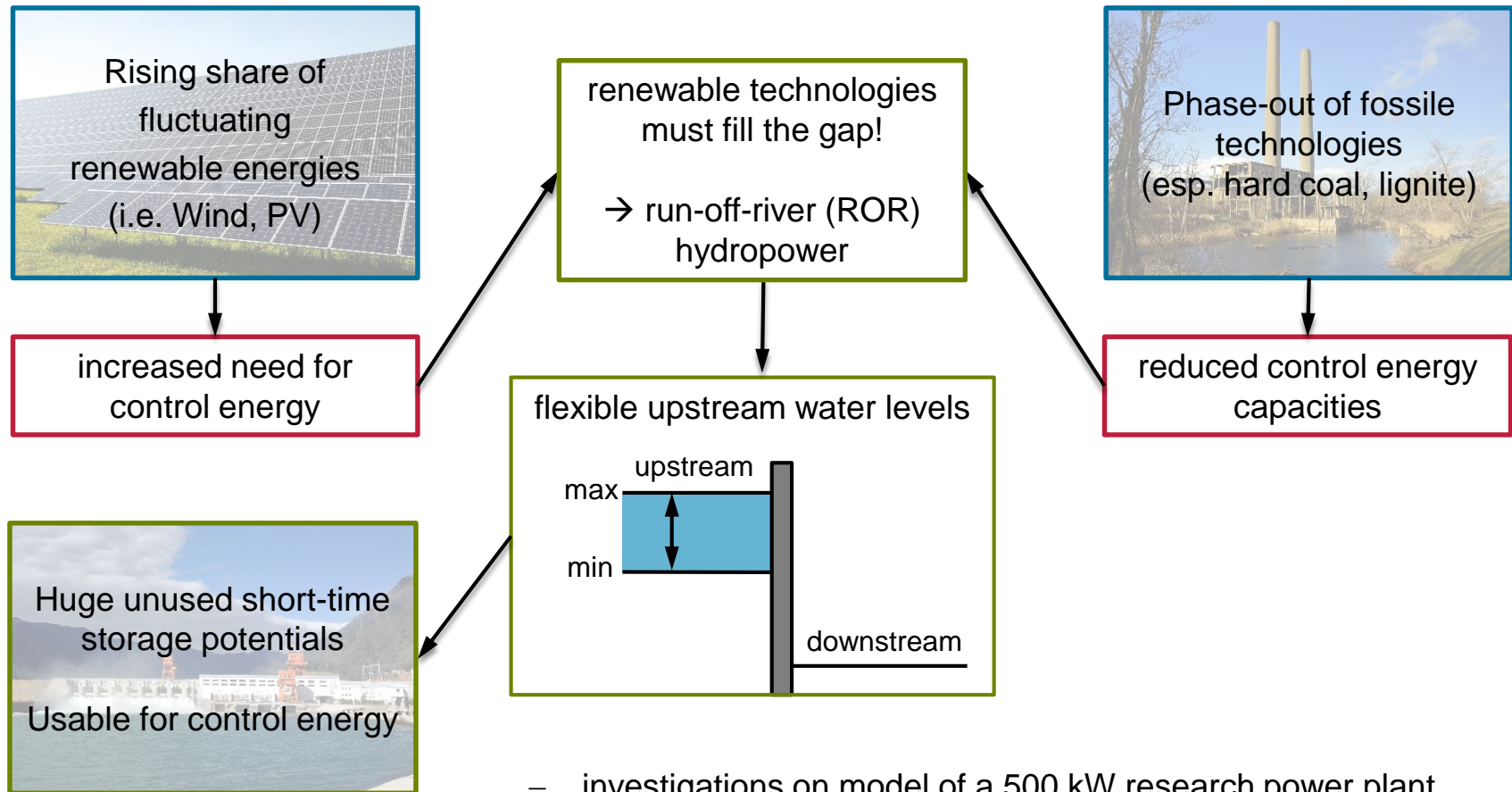
Technische
Universität
Braunschweig



Using Short-Time Storage Potentials of Run-of-River Hydroelectric Plants for Frequency Control

Bastian Hase, 6th International Conference on Smart Energy Systems
6-7 October 2020

Why using ROR-hydropower for producing control energy?

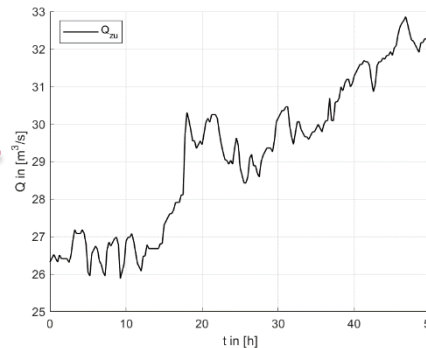


- investigations on model of a 500 kW research power plant with low head (1.76 m)
- maximum allowed amplitude of reservoir level: 0.27 m

How to make use of the short term storage potentials?

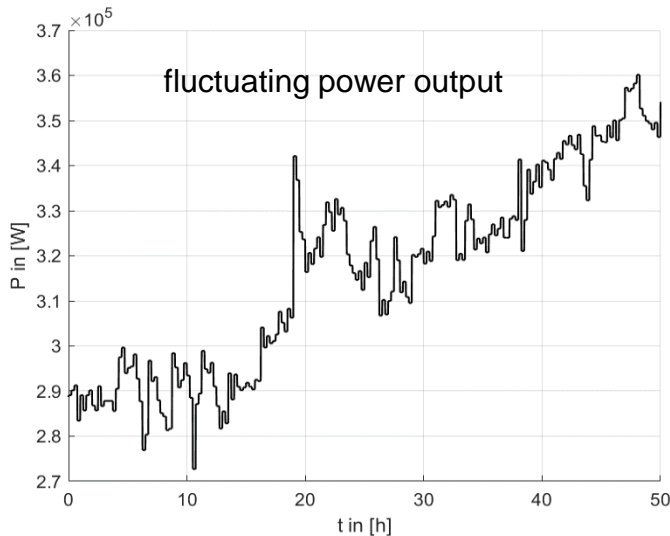
conventional operation
(quasi steady state)
constant reservoir level
flow rate machine
= flow rate river
1 product
(energy only)

variable flow rate into reservoir

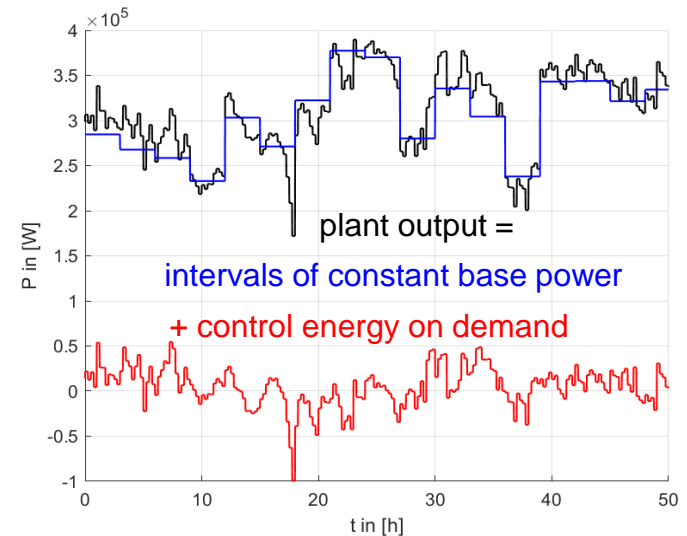


optimized operation
(using short term storage)

- variable reservoir level
- flow rate machine
≠ flow rate river
- 2 products (base power + control energy)



→ production follows flow rate



→ production scheduled in advance,
behavior similar to conventional plants!

Design of the plant model

Static modelling approach
 → plant dynamics and hydrodynamics neglectect

Upstream reservoir level $h_U(t)$ given by ODE:

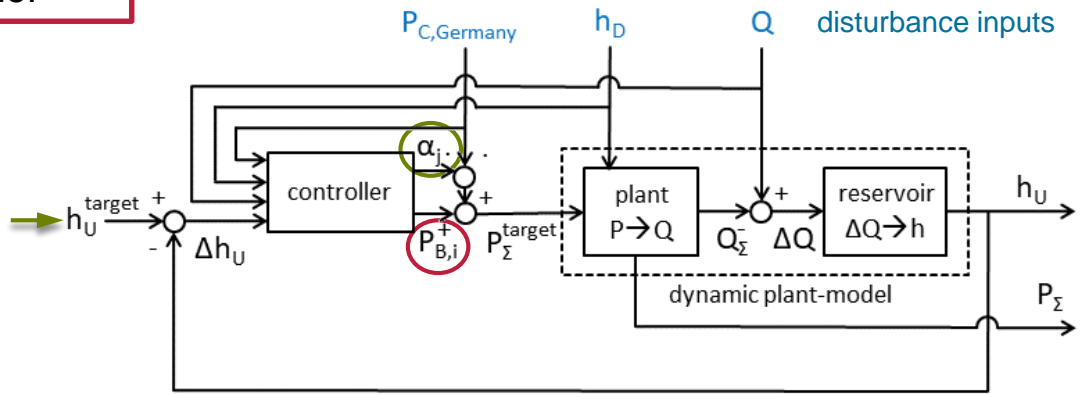
$$\dot{h}_U(t) = \frac{Q(t)}{A_{res}} - \frac{P_{B,i} + \alpha_j \cdot P_{C,Germany}(t)}{(h_U(t) - h_D(t))} \cdot \frac{1}{A_{res} \cdot \rho \cdot g \cdot \eta}$$

$Q(t)$	river flow rate
A_{res}	area of reservoir surface
$P_{B,i}$	base power during interval i
$h_D(t)$	downstream water level
ρ	density of water
g	earth acceleration
η	efficiency (assumed const.)
$P_{C,Germany}$	total control power activated in Germany

when driving with constant base power $P_{B,i}$
 upstream water level behaves unstable!

controller

- regularly adapts base power $P_{B,i}$
- determines maximum control power capacity for each tender interval α_j



Challenges for the controller

Controller needs to estimate disturbance inputs over a long time

$P_{C,Germany}$: positive and negative control power approximately compensate

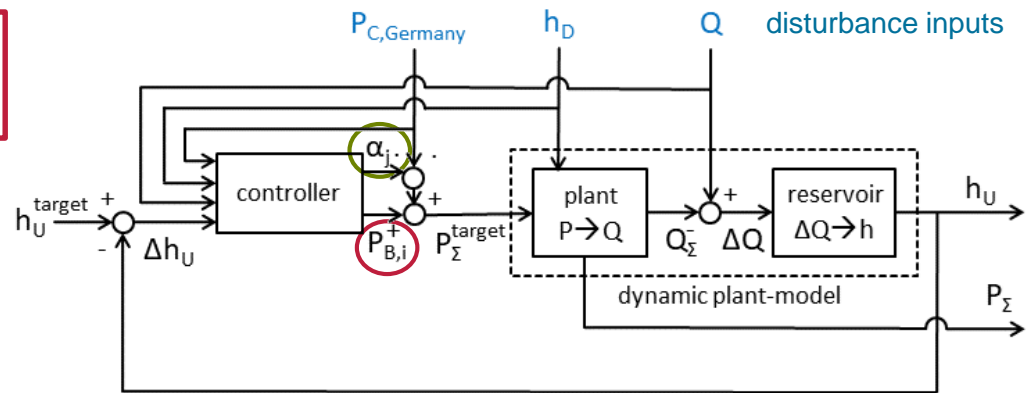
h_D : Can be calculated via rating curves (from Q_Σ)

Q : Precise forecast difficult
High influence on upstream level!

controller must guess future values
 → long intervals reduce reliability

short term storage potentials
 $\approx 48 \text{ min} \cdot MQ$ (mean flow)

type	lead time	delivery time
FCR	129 h	168 h
aFRR	9 h	24 h
mFRR	14 h	24 h
intraday	5 min	>15 min
day ahead	12 h	> 1h



Control energy potentials

investigation period: 2015-2017

mean ROR-coverage of national demand¹:

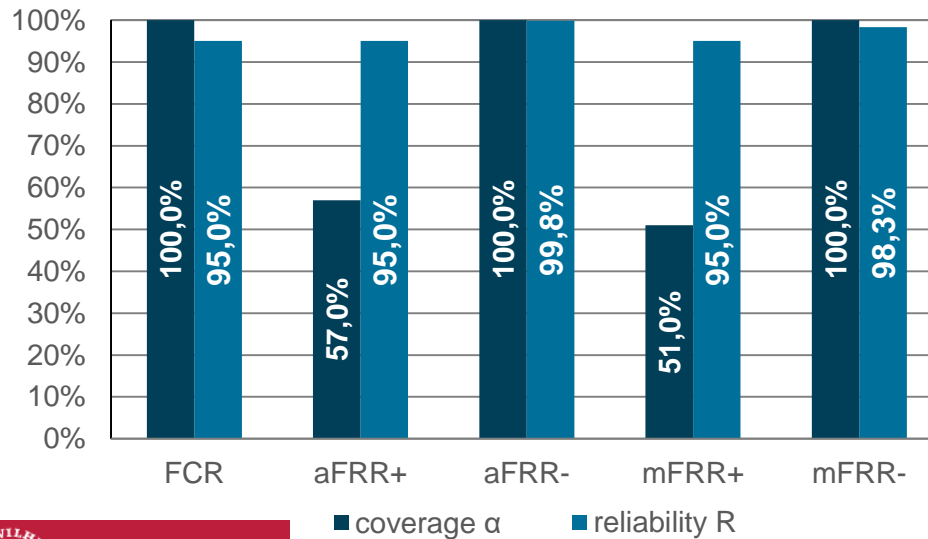
$$\alpha^{+/-} = \frac{W_C^{+/-}}{W_{C,Germany}^{+/-}} \cdot \frac{P_{Germany}}{P_{max}}$$

reliability:

$$R^{+/-} = \frac{W_C^{+/-}}{W_{C,target}^{+/-}}$$

high coverages α lead to reduced reliability R

W_C	plant's control energy production (2015-2017)
$W_{C,Germany}$	national control energy demand (2015-2017)
P_{max}	plant's rated power
$P_{Germany}$	non swelling ROR-capacity in Germany
$W_{C,target}$	total control energy demanded from plant



high potentials for all three types of control energy!

positive control power: backups required!

Key findings

ROR important servant to the future energy system!
 → 3 % energy production vs. >50% of FRR potential

already low reservoir amplitudes
 < 30 cm feasible for storage

base power marketing feasible with:

- lead time $t_L = 1h$
- time of constant delivery $t_D = 3h$
- reliabilities $R_B > 99.8\%$

potentials for negative FRR >> positive FRR
 → due to limited storage and power reserves

decreasing tender intervals for aFRR (07/2018)
 significantly increases reliability of control energy

aFRR at $(\alpha^+, \alpha^-) = (50\%, 100\%)$			
tender	weekly	daily	increase
reliability (+)	89.78%	97.17%	7.14%
reliability (-)	98.41%	99.83%	1.42%

in case of positive prices:
 negative aFRR generates additional revenues

current flow-model: even daily tenders
 beyond forecast period of controller

Outlook and further areas of research

objectives

actions

refining of the model
→ increased accuracy

higher resolution of input data
(currently 15 minute averages)

including inertia, machine dynamics
and working points of the plant

including hydrodynamics of plant and
riverbed

improving controller
→ increased potentials

improved flow prediction by

- optimized hydrologic models
- including weather forecast
- machine learning

validation of simulated model on a real
power plant

voluntary plant
owners welcome!