THE UNIVERSITY OF QUEENSLAND AUSTRALIA | CREATE CHANGE

Smart Urban Water Systems

- some preliminary thoughts

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Advanced Water Management Centre

Why do I feel passionate about it?

Beijing University of Aeronautics and Astronautics

Ghent University & The University of Queensland

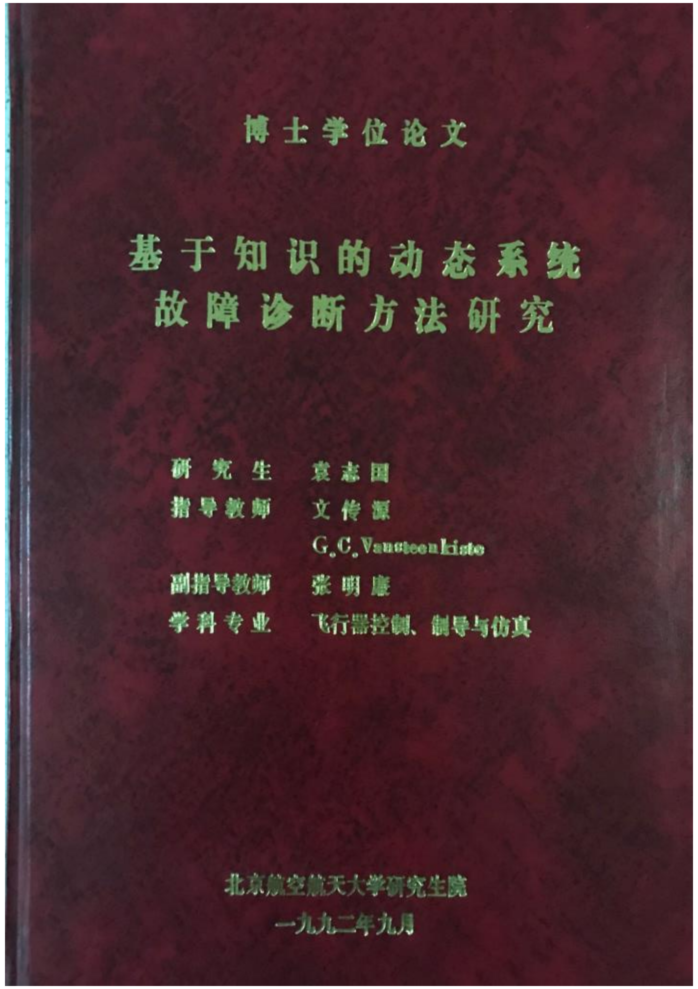
My Bachelor (1985)
Sensors & instrumentation

My PhD (1992)
Automation (AI)

My career to date
Urban water management

Smart urban water systems

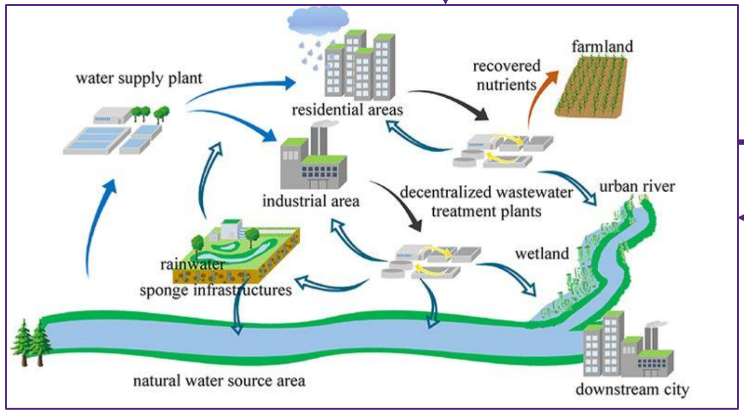
Knowledge-based fault diagnosis in dynamic systems
(Yuan, Z. PhD thesis, 1992)



Smart Urban Water Systems

Operational/managing/planning decisions

Planners
Managers
Operators
Customers



Real-time control

Sensing
Local control
Transmissions
…

Supervisory control

Data storage
Data analytics
Optimization
…

Learned status
Recommended strategies
…

IoT sensors
Network communication
…

Computing power
Machine learning
Artificial intelligence
…

Smart water system vs. ICA

- Smart water system encompasses ICA

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Review

Sweating the assets – The role of instrumentation, control and automation in urban water systems

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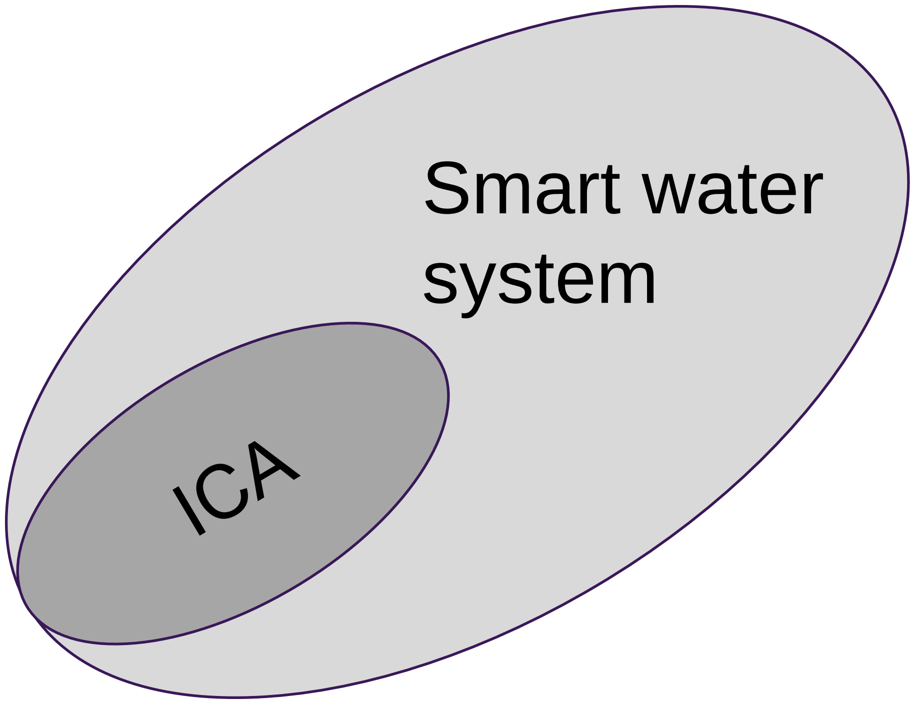
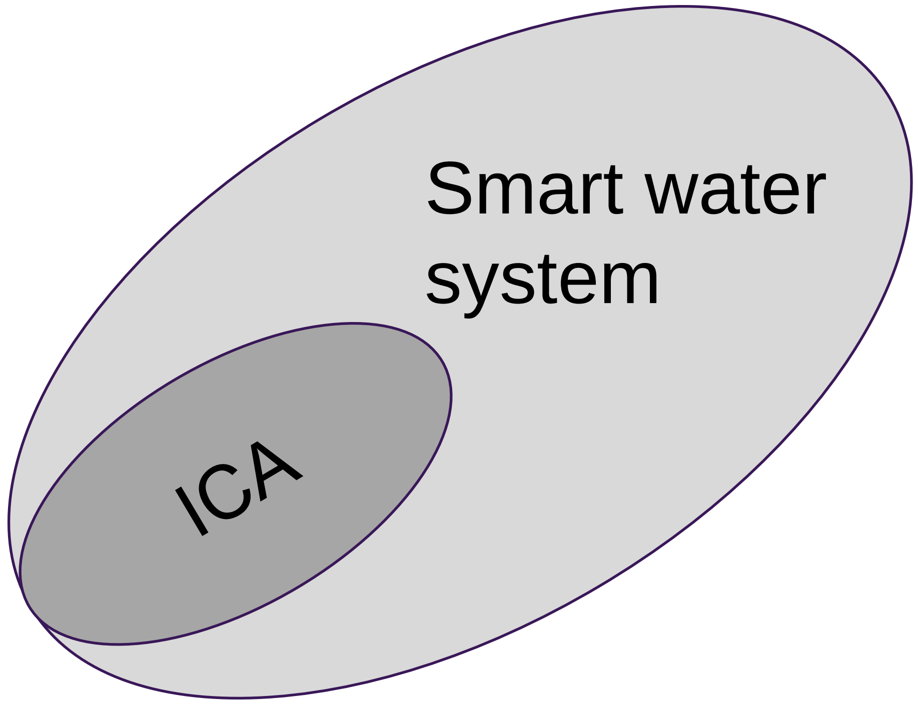


ICA: Instrumentation, control and automation

Smart water system vs. ICA

- Smart water system encompasses ICA

  but expanding towards
- higher levels of duties
  - More integrative
  - More supervisory
  - Decision support (operational, management and planning, behaviour change)
- higher level of intelligence
  - IoT sensors
  - Big data
  - Machine learning & artificial intelligence

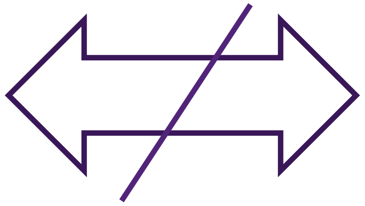


ICA: Instrumentation, control and automation

Driving forces for smart urban water

Technology push

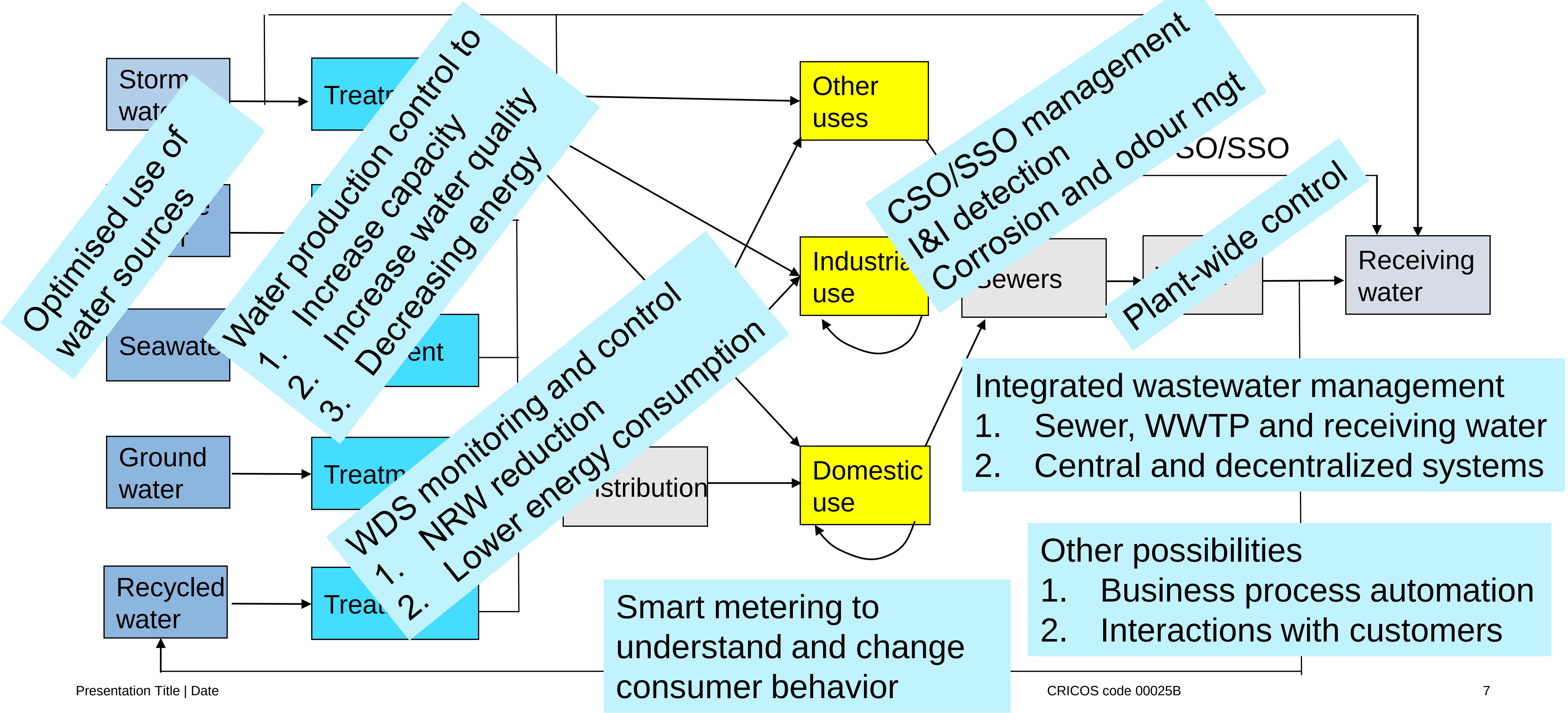
- Internet of Things
- Low-cost sensors and low-cost, yet powerful microchips
- Large data storage capabilities
- Fast computing e.g. iCloud computing
- Advanced data analytics
  - machine learning
  - artificial intelligence



Demand pull

- Population growth and continued urbanisation imposes more pressure to urban water systems
- Climate change causes more variability
- Aging infrastructure
- Customer expectation
- Integrated urban water management is becoming more important

Where are the opportunities (non-exhaustive)



Example 1: water source optimization – the orange council case study

Several water sources

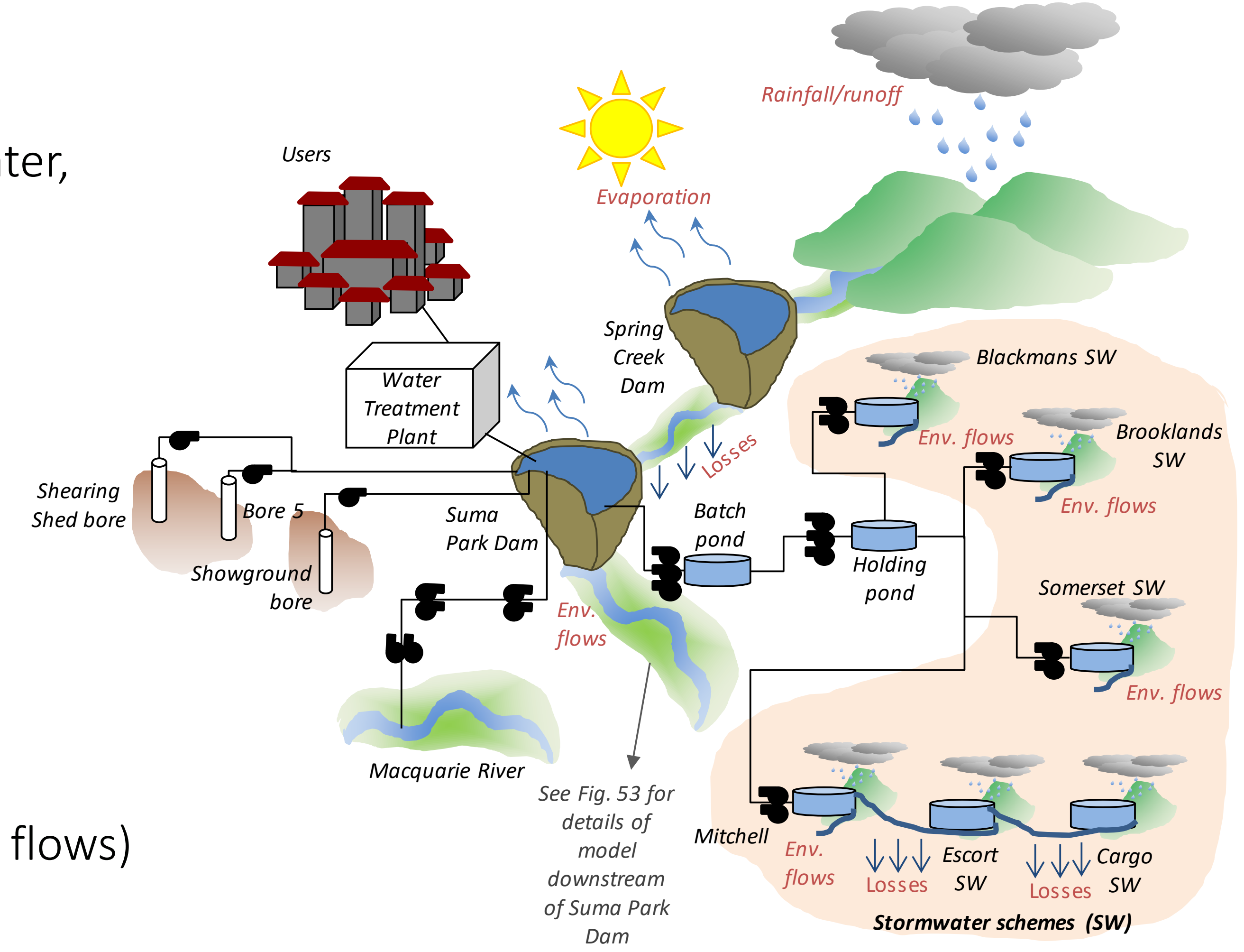
(natural catchments, groundwater, stormwater harvesting and Macquarie River)

Several constraints

(environmental flows, source withdrawal limits, water restrictions)

Several objectives

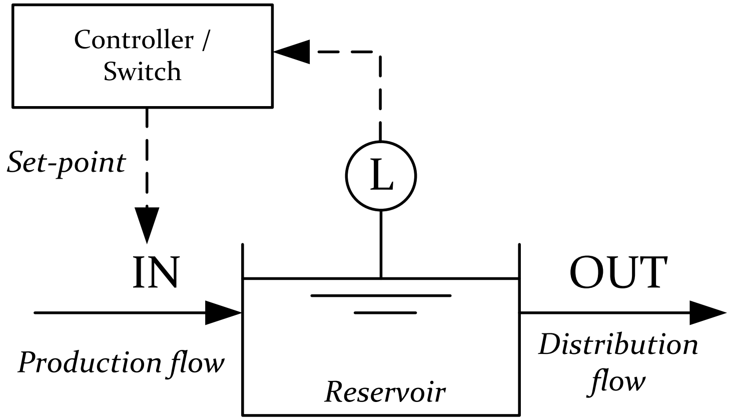
(minimisation of costs, spill, greenhouse gas emissions and maximisation of environmental flows)

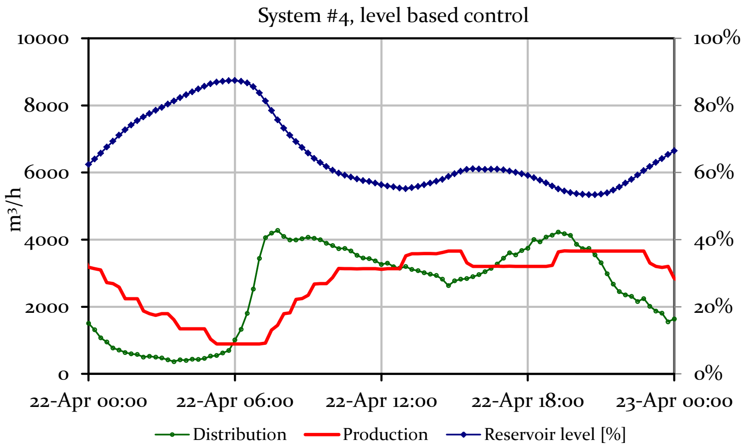


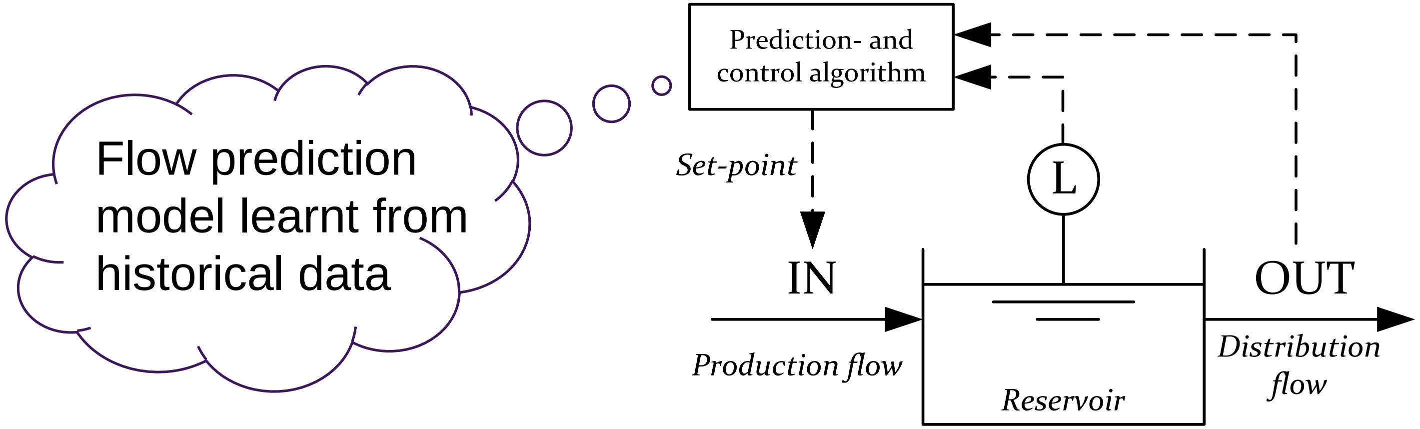
Dr Lisa Blinco, Uni Adelaide

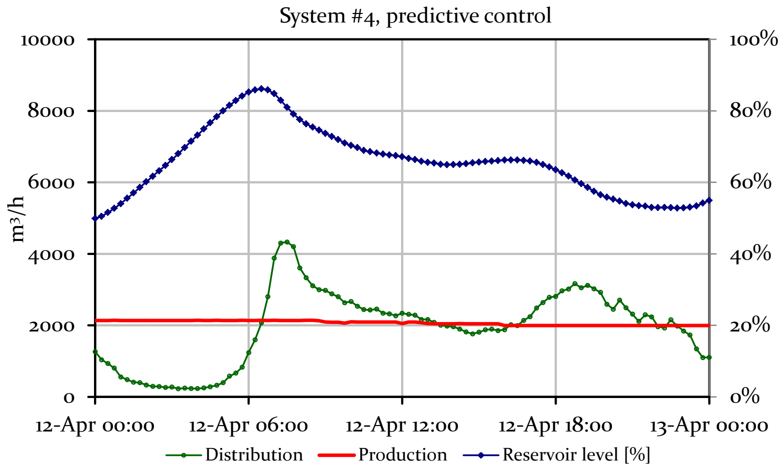
Example 2: water production based on demand prediction

Bakker et al. (2013)

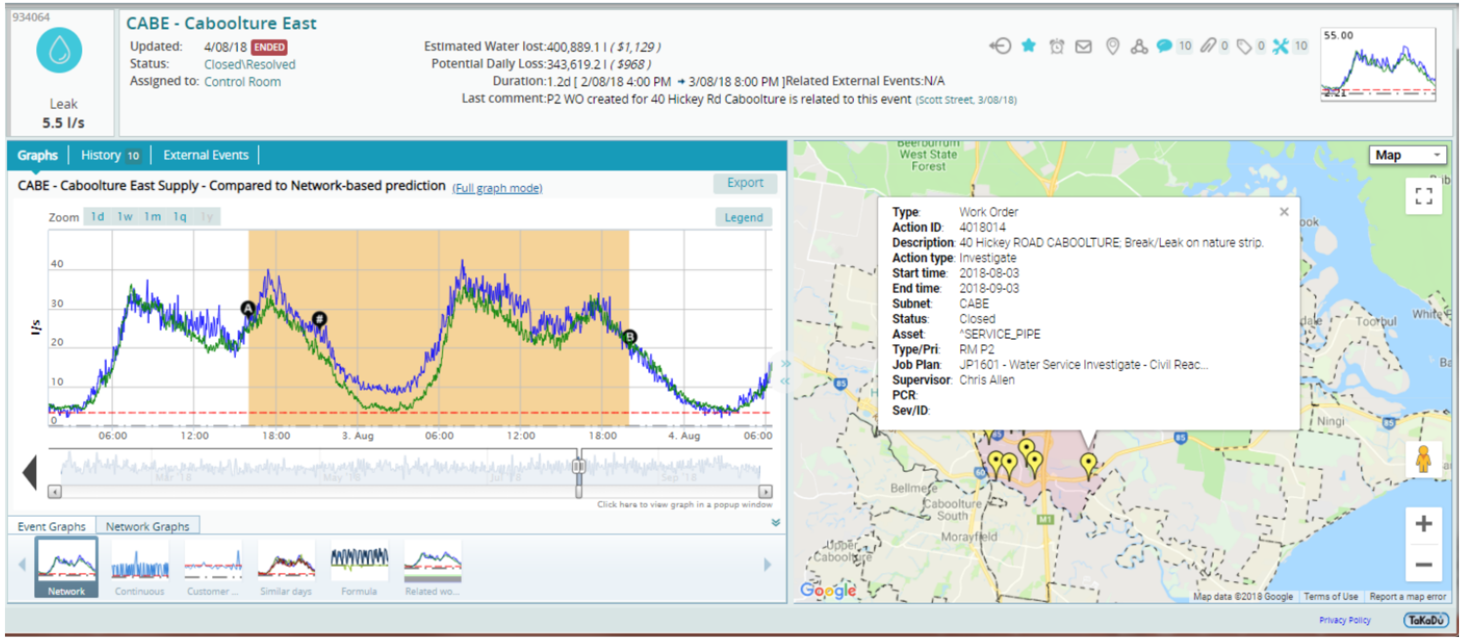








Example 3: tackling non-revenue water



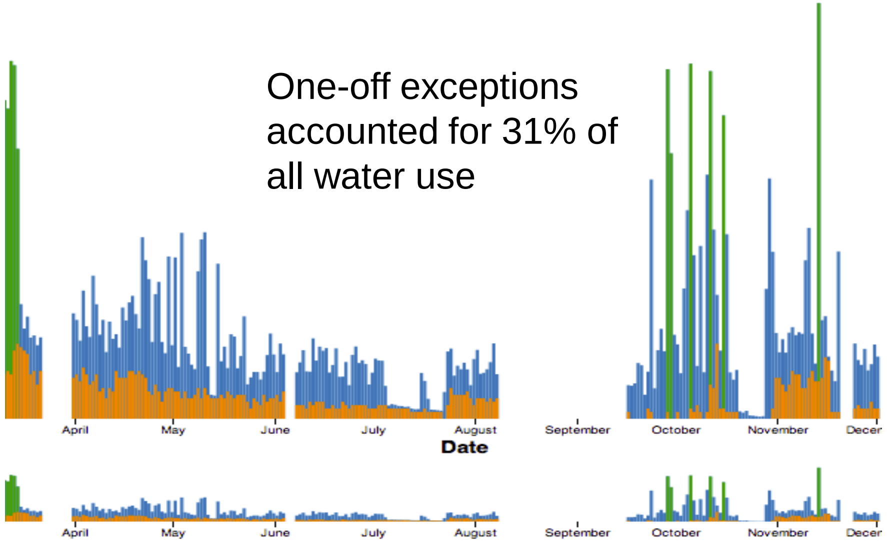
Location	Performance Indicators (Last month) Estimated water loss	Volume per connect...	Technical effici...	ILI (August / Se...	Total Consumptio
LAGHL - Laguna HLZ	0.00 l	N/A	100.00 %	N/A / N/A	0.90 / 0.00 Ml
EOH9P - Mango Hill East	233,910.73 l	N/A	100.00 %	N/A / N/A	7.18 / 3.70 Ml
DMA04R - Margate Zone	1.03 Ml	495.76 l	94.80 %	0.46 / 0.69	0.74 / 0.00 Ml
DMA56P - Ferny Hills South	155,029.50 l	474.75 l	95.19 %	0.96 / 0.62	0.00 / 0.00 Ml
CASWY - Castaways Beach	151,202.67 l	716.36 l	100.00 %	0.00 / 0.00	0.04 / 0.00 Ml
DMA01P - BRENDALE Strathpine East	3.32 Ml	1,719.83 l	79.75 %	7.01 / 5.67	4.76 / 0.70 Ml
CABN - Caboolture North	2.31 Ml	521.50 l	85.54 %	0.86 / 0.82	10.41 / 0.00 Ml
DMA38P - Dayboro LL	0.00 l	N/A	100.00 %	N/A / N/A	0.00 / 0.00 Ml
LAN03 - Diddillibah	0.00 l	N/A	100.00 %	N/A / N/A	0.00 / 0.00 Ml
DMA31P - Warner Central	0.00 l	N/A	N/A	N/A / N/A	0.94 / 0.00 Ml
DMA59P - Highvale South	693,370.63 l	N/A	100.00 %	N/A / N/A	3.66 / 1.22 Ml

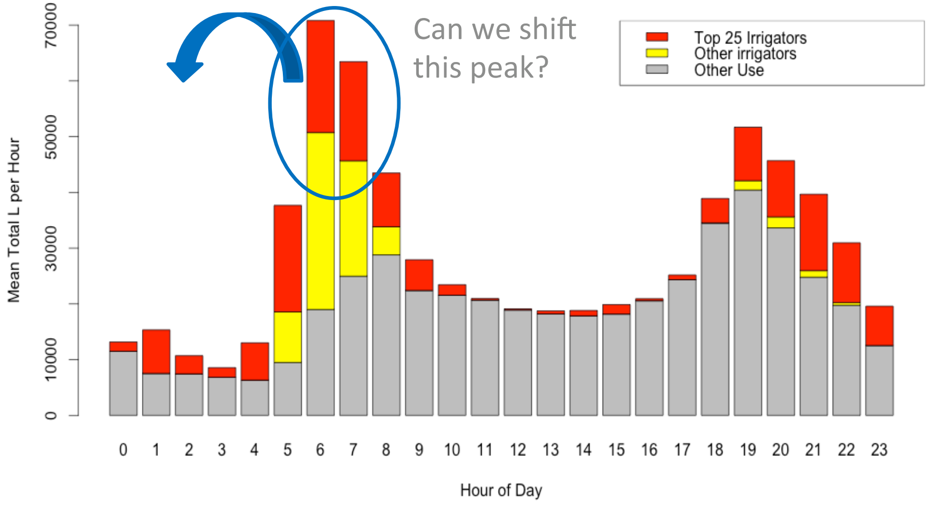
Total: 194, Displayed: 180

Example from Unitywater (QLD) potable water distribution network using TaKaDu platform (Israel):

- Real-time flow data versus Network-based prediction flow model = leak detection shortly after burst & detection of hidden (underground) leaks
- $16 million AUD per annum in savings from early detection of leaks
- 6.5 billion litres of non-revenue water loss prevented in 2017 due to enabling of rapid, fit-for-purpose and localised response

Example 4: water consumption pattern analysis – changing customer behavior





14,000 smart meters installed

Prof Rachel Cardell-Oliver, UWA

Example 5: online optimization of pump operations

Odour control at inlet of a WWTP

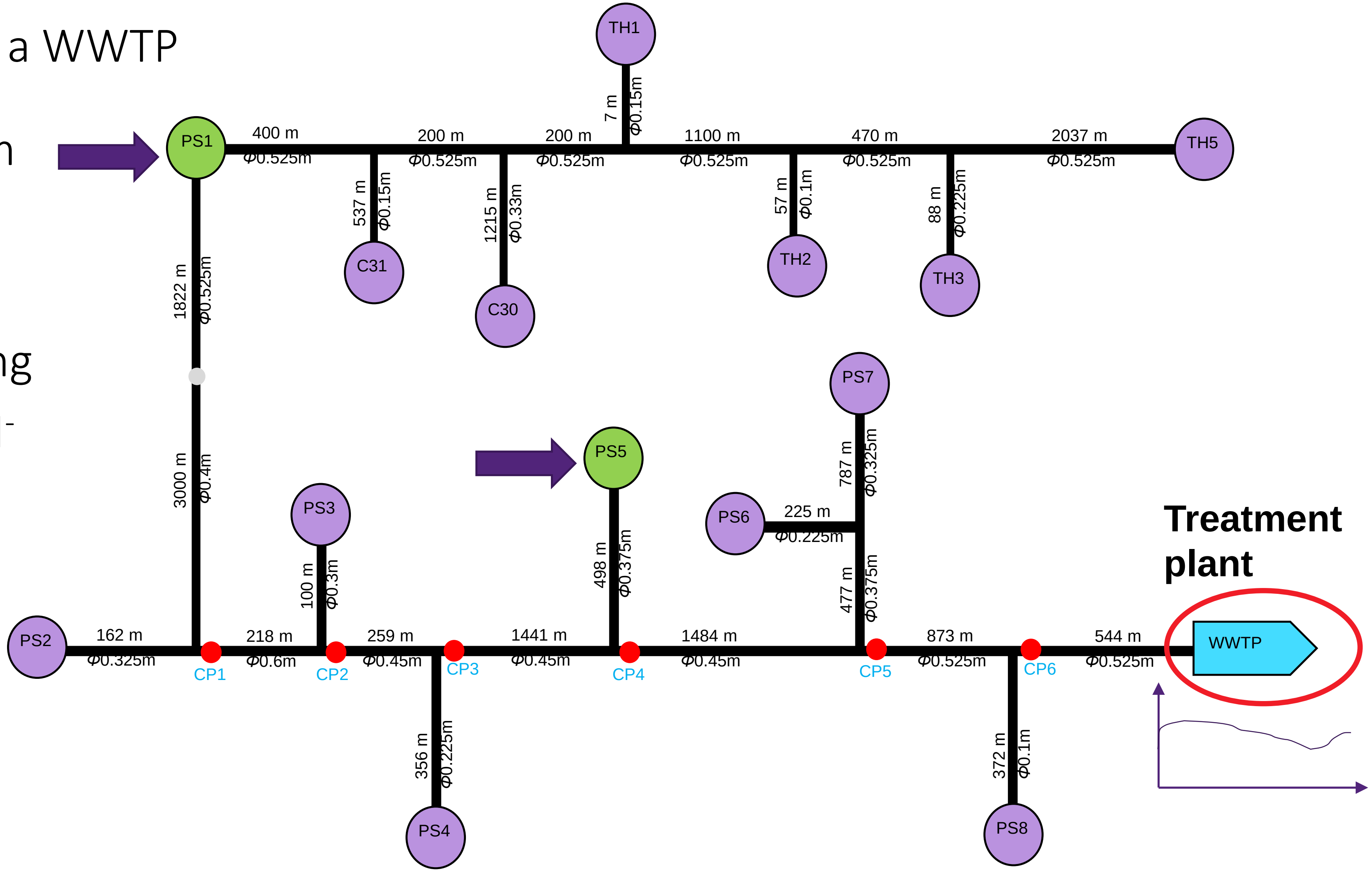
13 pump stations; 26 km

ADWF = 14.3 ML/day

Magnesium dosing

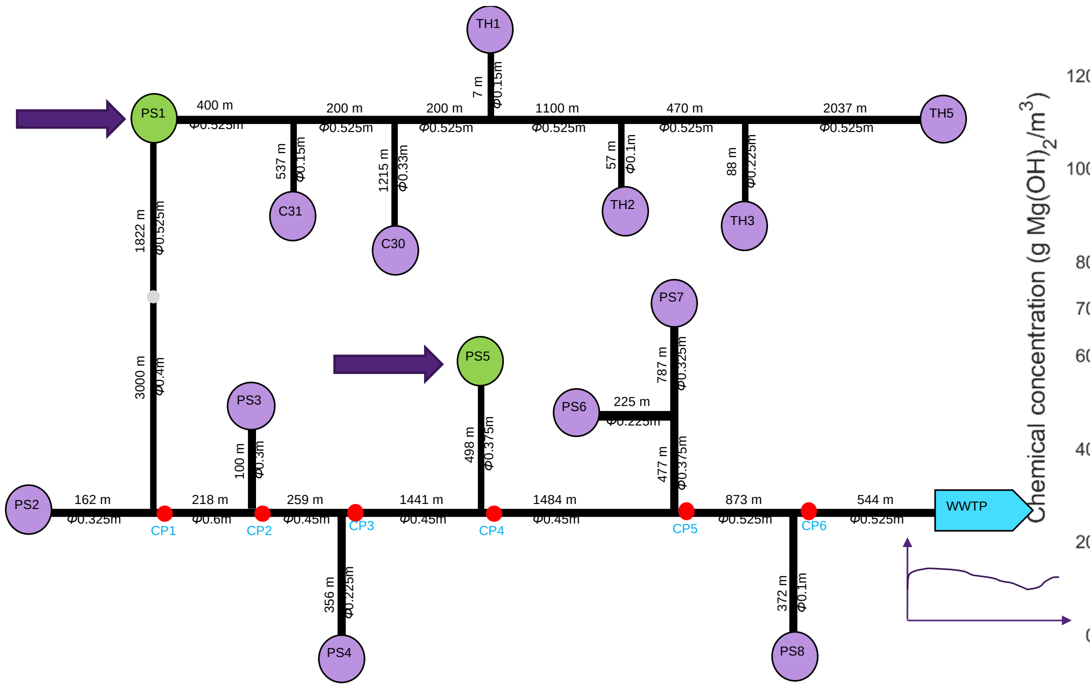
$$Mg(OH)_2 \rightleftharpoons Mg^{2+} + 2OH^-$$

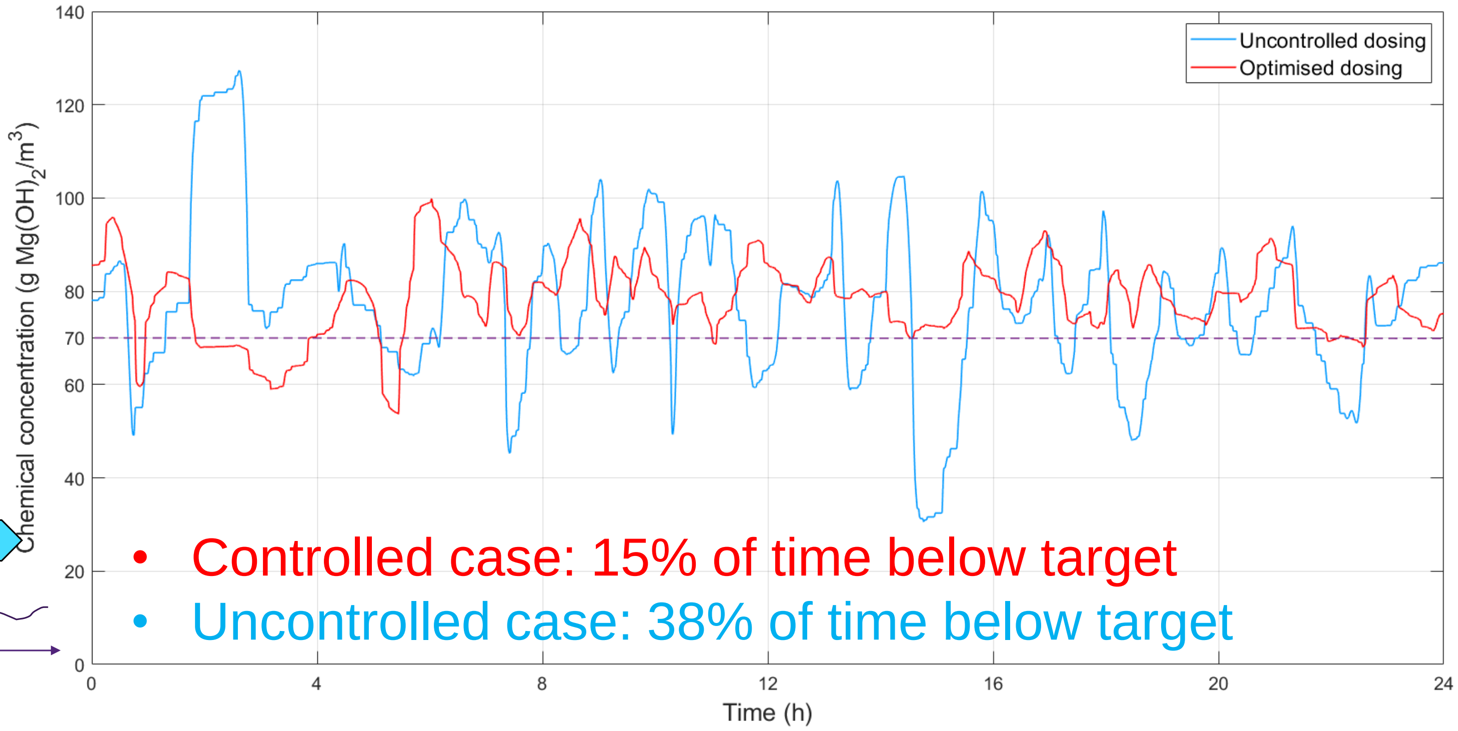
$$H_2S \rightleftharpoons HS^- + H^+$$



Example 5: online optimization of pump operations

Odour control at inlet of a WWTP





- Controlled case: 15% of time below target
- Uncontrolled case: 38% of time below target

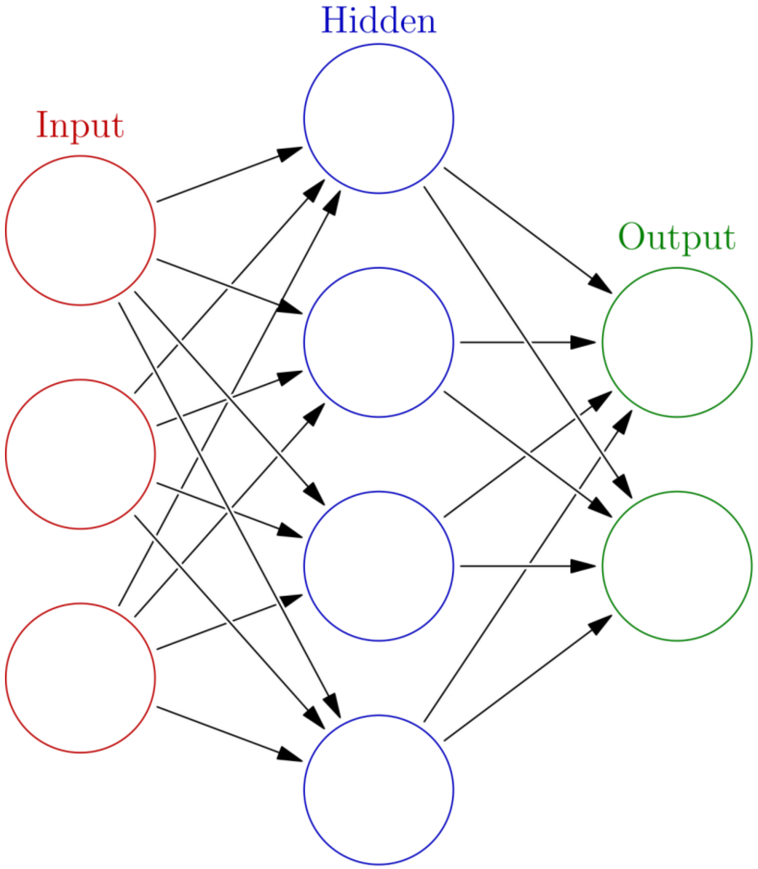
- Hybrid system – linear model predictive control algorithm not directly applicable
- Large search spaces – efficient optimization algorithms required

Machine learning

- Block-box (data driven)
  - Statistical modelling
  - Artificial neural network
  - Large amount of data
  - Identifiability issue

ARMAX model:

$$A\left(z^{-1}\right)y\left(t\right)=B\left(z^{-1}\right)u\left(t\right)+C\left(z^{-1}\right)e\left(t\right)$$



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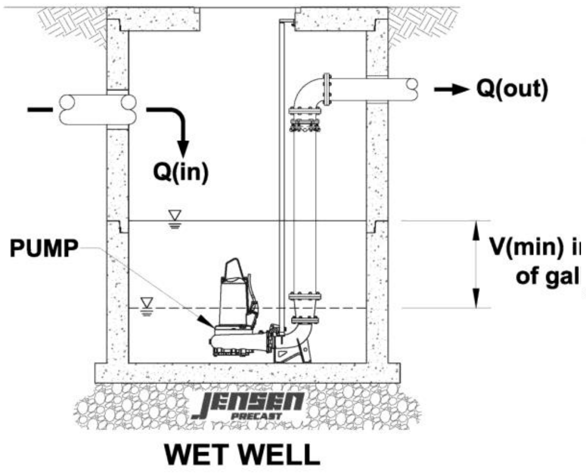
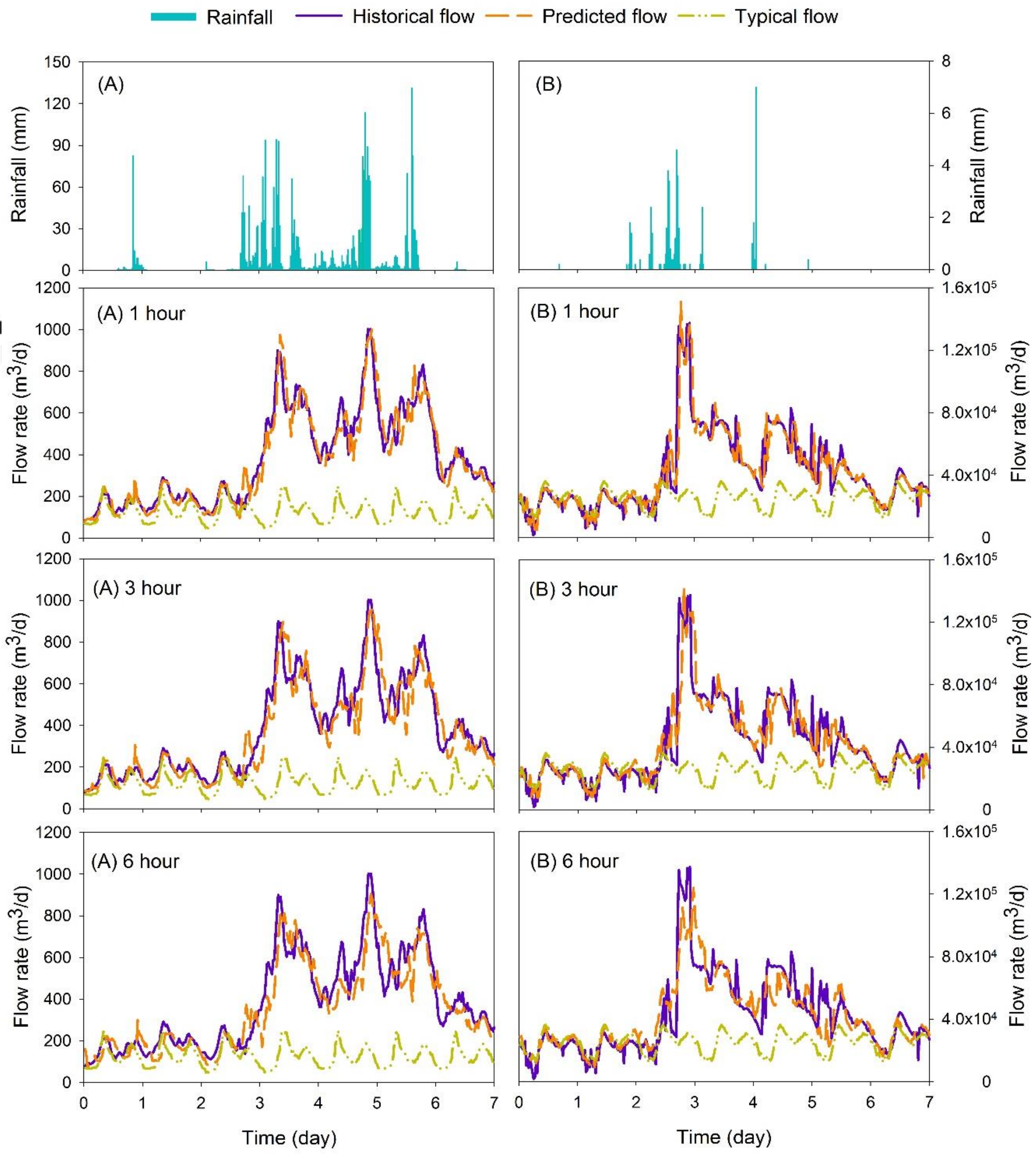


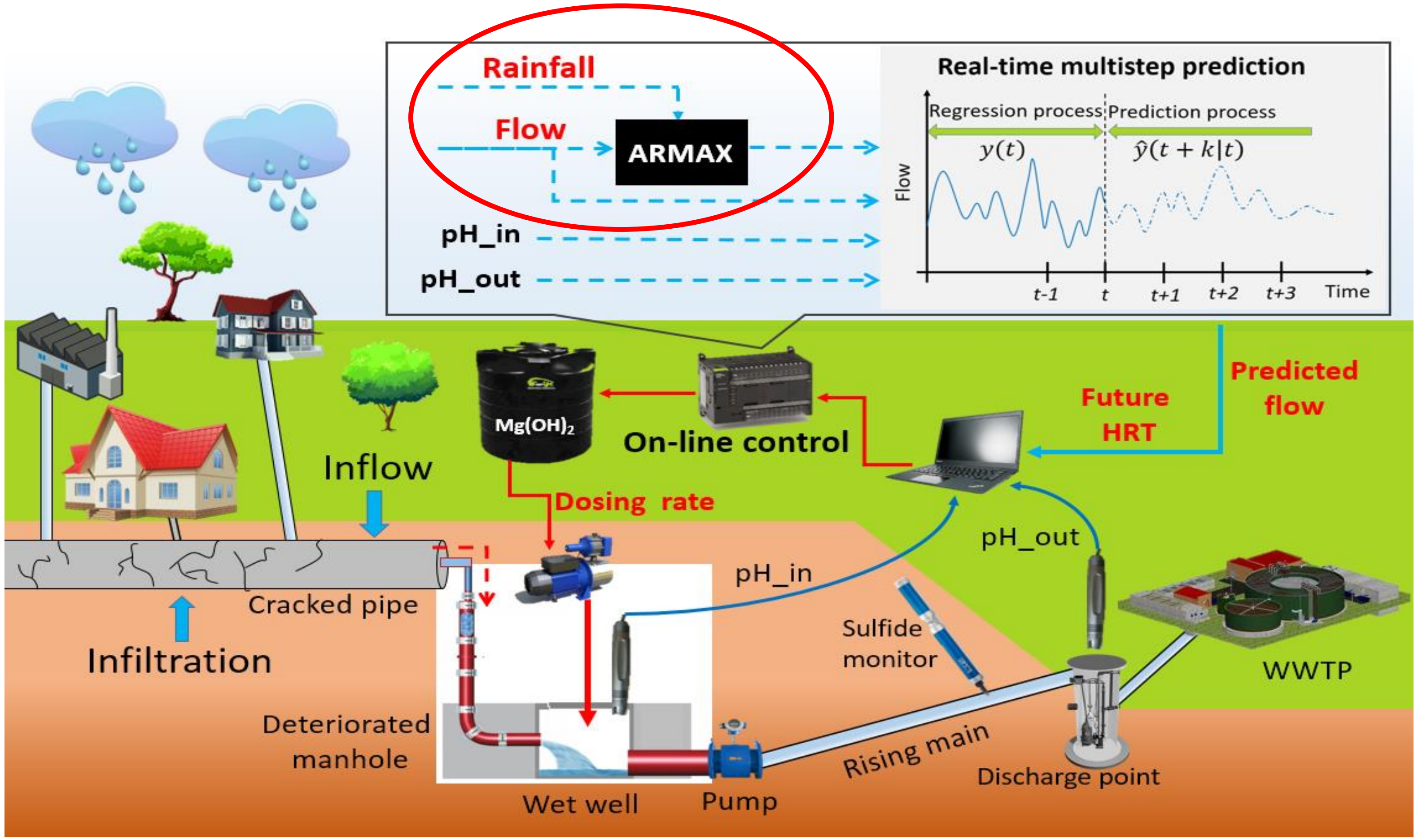


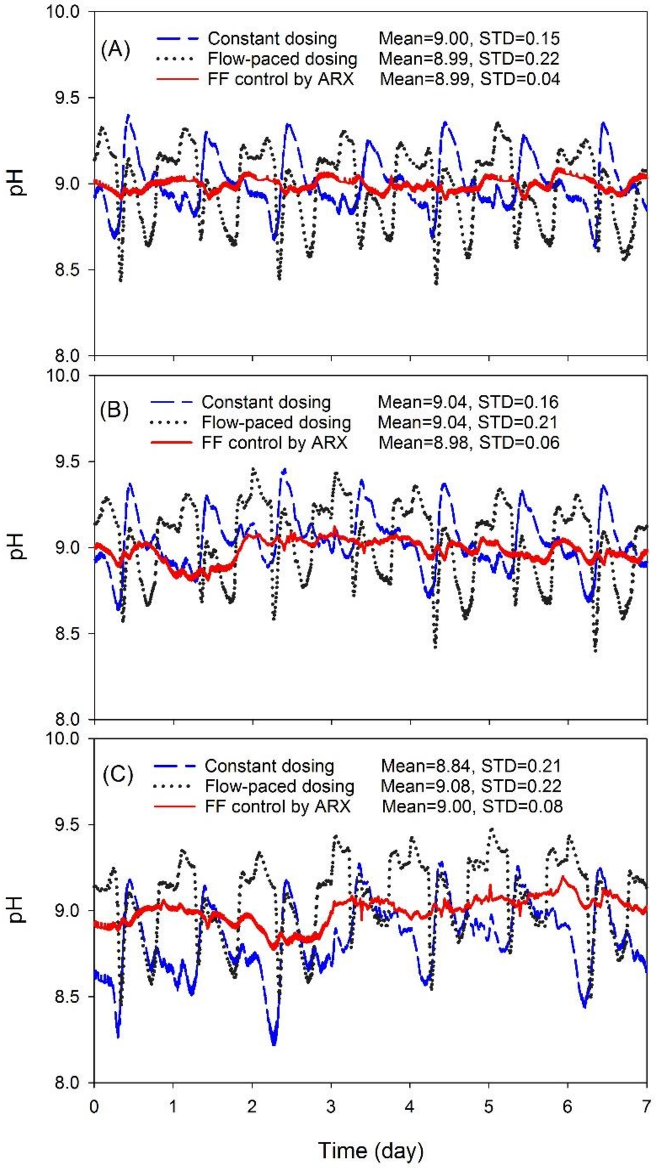
ARMAX model:

$$
\begin{aligned}
\hat{y}(t) = {} & 0.2140\hat{y}(t-1)+0.1822\hat{y}(t-2)+0.1018\hat{y}(t-3)+0.1634\hat{y}(t-4)+ \\
& 0.1014\hat{y}(t-5)+0.0869\hat{y}(t-6)+0.0543\hat{y}(t-7)+1.5261u(t-1)+ \\
& 0.7946u(t-2)-0.0285u(t-3)+0.2921u(t-4)+e(t)
\end{aligned}
$$

Li et al. (2019)

Machine learning





Machine learning

- Block-box (data driven)
  - Statistical modelling
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  - Large amount of data
  - Identifiability issue
- Grey-box
  - Data supplement existing knowledge
  - Model-supported data analysis or data-enabled model identification
  - Process knowledge required
  - Smaller amount of data needed

Prior knowledge is important

We should not ask the machine to invent the Bernoulli equation!

$$\frac{\partial(\rho\eta)}{\partial t} + \frac{\partial(\rho\eta u)}{\partial x} + \frac{\partial(\rho\eta v)}{\partial y} = 0,$$

$$\frac{\partial(\rho\eta u)}{\partial t} + \frac{\partial}{\partial x}\left(\rho\eta u^2 + \frac{1}{2}\rho g\eta^2\right) + \frac{\partial(\rho\eta uv)}{\partial y} = 0,$$

$$\frac{\partial(\rho\eta v)}{\partial t} + \frac{\partial(\rho\eta uv)}{\partial x} + \frac{\partial}{\partial y}\left(\rho\eta v^2 + \frac{1}{2}\rho g\eta^2\right) = 0.$$

Machine learning

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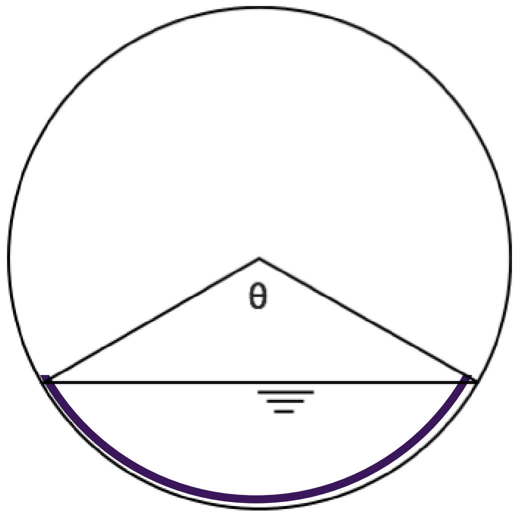

D: diameter
s: slope
Q: flow rate
T: temperature

$$k_{CH4,T} = a_1 T^{b_1} + a_2 Q^{b_2} + a_3 D^{b_3} + a_4 s^{b_4}$$

$$k_{CH4,T} = k(T) Q^{\alpha} D^{\beta} s^{\gamma}$$

Segmented efforts need to be united

WHAT UTILITIES WANT TO ACHIEVE?
(DEMAND PULL)

WHAT DO TECHNOLOGIES OFFER?
(TECHNOLOGY PUSH)

SHARED OBJECTIVES

JOINT EFFORT

Concluding remarks

- Urban water system will get smarter!!
- While isolated case studies have been done, there is a lack of a systematic framework
- Collaborative efforts from utilities, hardware suppliers, software suppliers, and researchers needed
- Multi-disciplinary research is required

Acknowledgements