Using Neural Networks for Advanced Data Analytics and Operational Improvements

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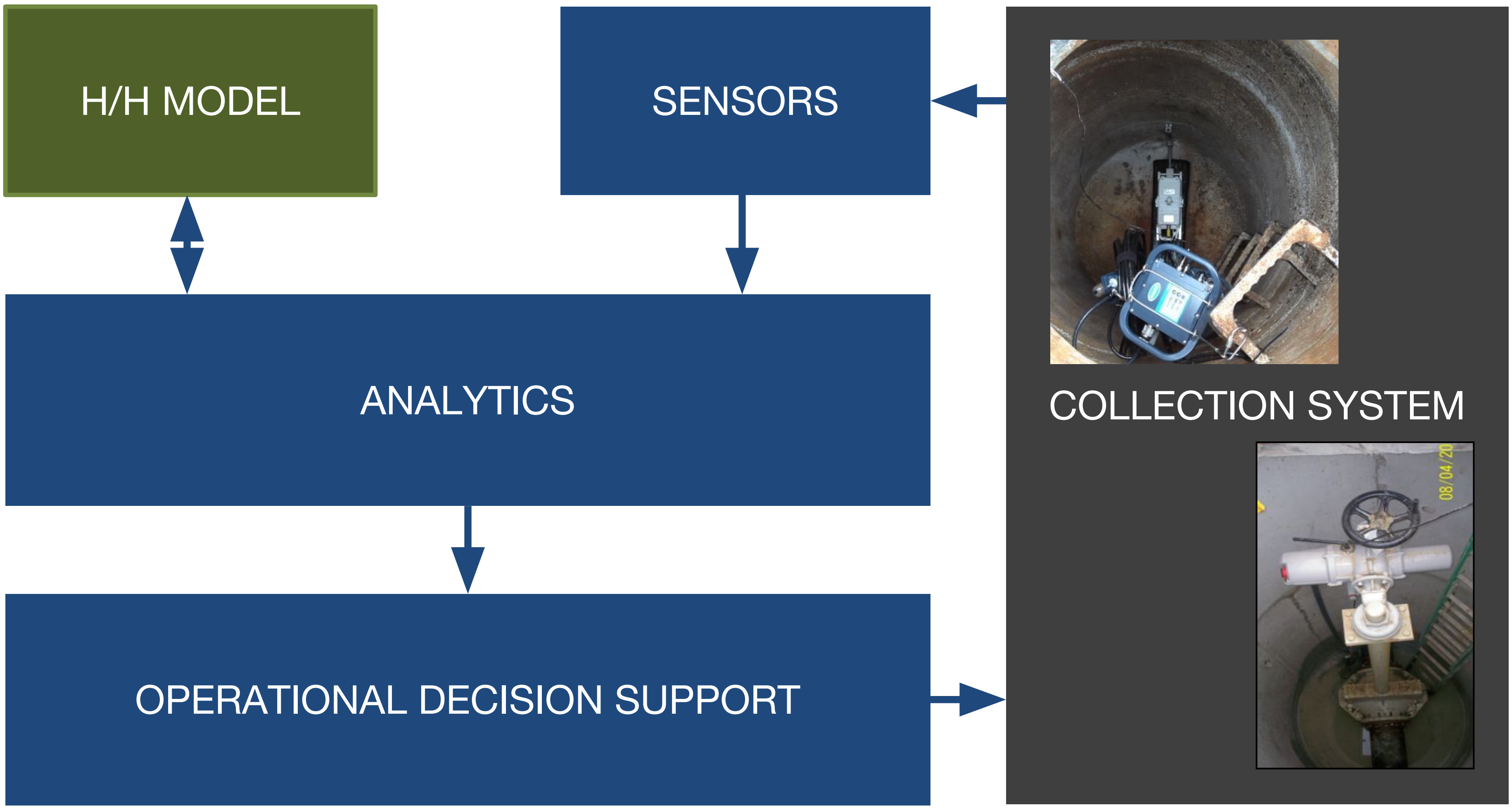
Collection Systems
2016

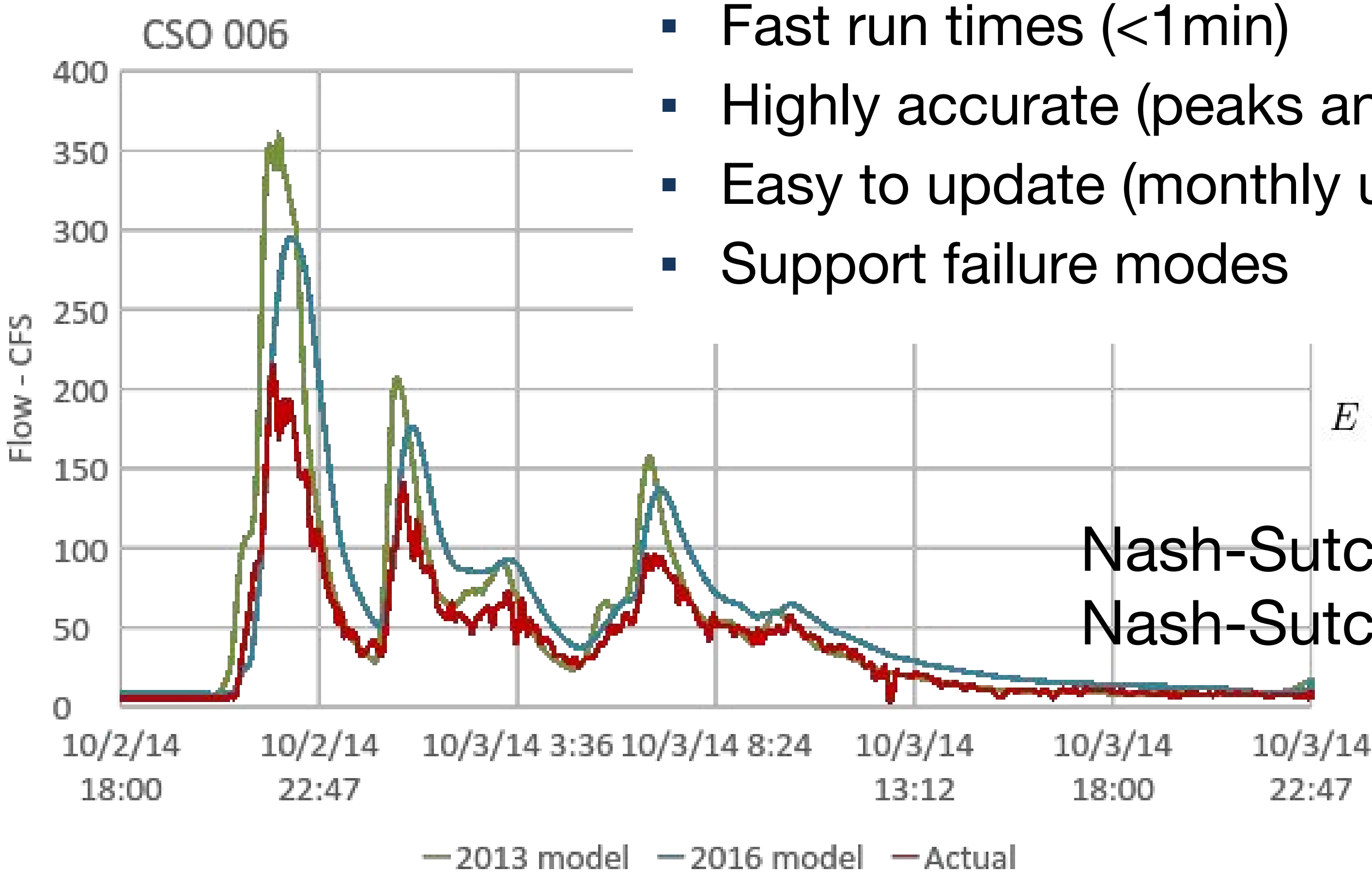
Real Time Decision Support System



Real Time Operational Model

Different objectives from planning model

- Fast run times (<1min)
- Highly accurate (peaks and volume)
- Easy to update (monthly updates)
- Support failure modes



$$E = 1 - \frac{\sum_{t=1}^{T}\left(Q_o^t - Q_m^t\right)^2}{\sum_{t=1}^{T}\left(Q_o^t - \overline{Q_o}\right)^2}$$

Nash-Sutcliffe 2013: 0.29

Nash-Sutcliffe 2016: 0.38

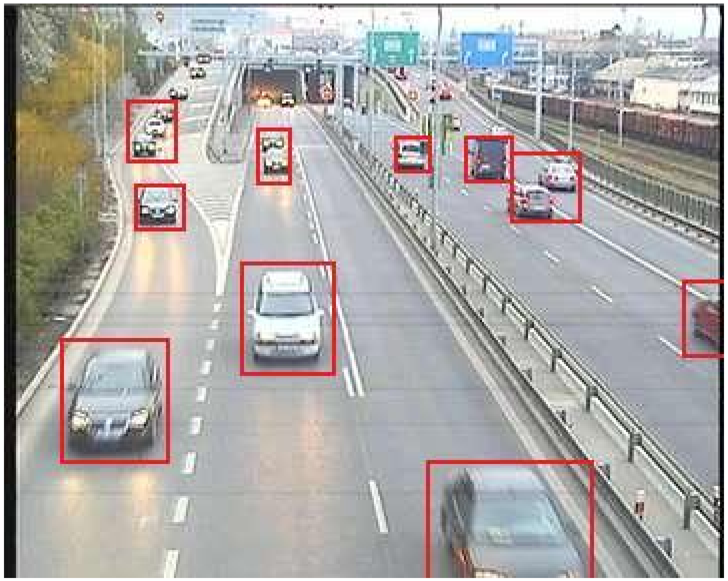
From Data to Model

Machine Learning:
"Study and construction of algorithms that can learn and make predictions on data" [1]

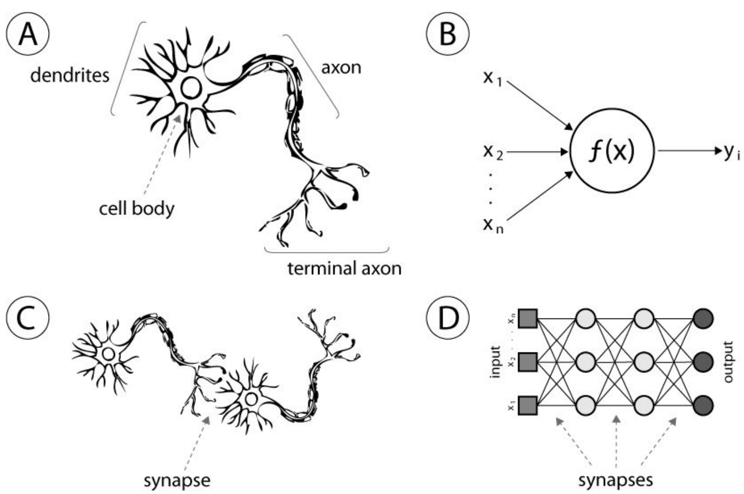
Neural Network:
"Machine Learning algorithm inspired on the way a human brain works"

[1] *Ron Kohavi; Foster Provost (1998). "Glossary of terms". Machine Learning **30**: 271–274.*

Artificial Neural Networks Applications



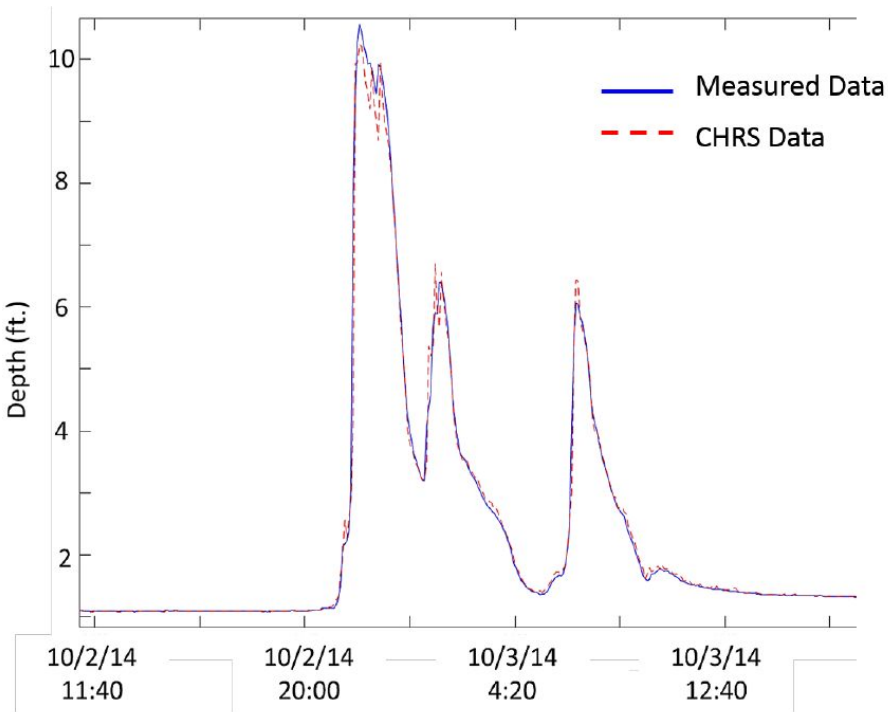
http://www.tsdconseil.fr/formations/dsp/opencv/index-en.html

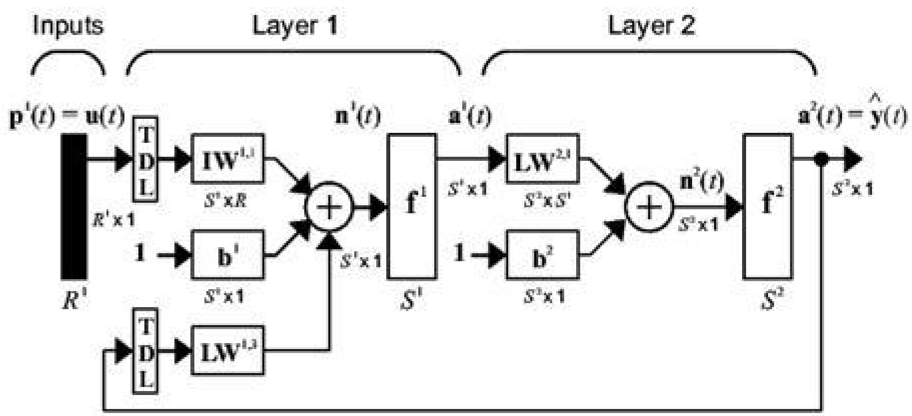


V.G. Maltarollo et. al, “Applications of Artificial Neural Networks in Chemical Problems”

- pattern recognition
- driverless cars
- crime prevention
- speech recognition
- medical diagnosis
- automated trading systems
- e-mail filtering

Cognitive Hydraulic Response System





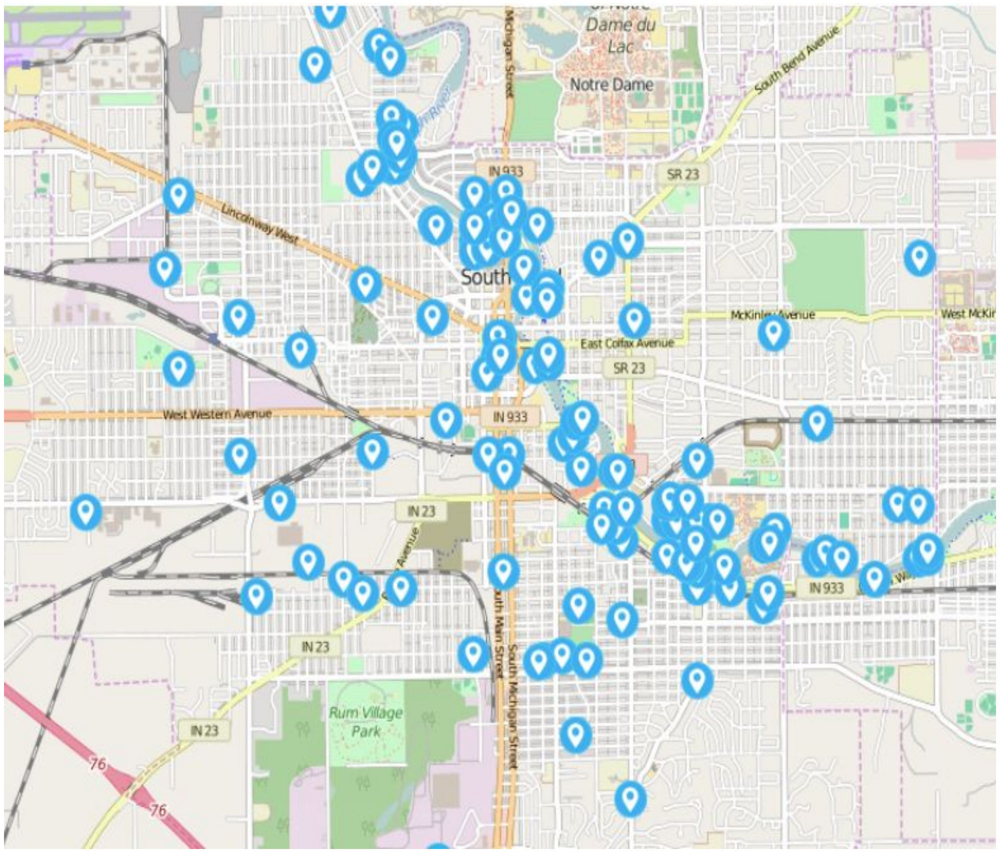
- Cognitive: it learns from observation
- Based on sensor data
- Utilizes self learning ANN
- Abstracts the H/H elements with most uncertainty

Real Time Modeling starts with Real Time Monitoring

Case Study: Lick Run Basin, Cincinnati, OH

- 4 sq.miles of CSS
- 11 flow monitors
- 3 rain gauges

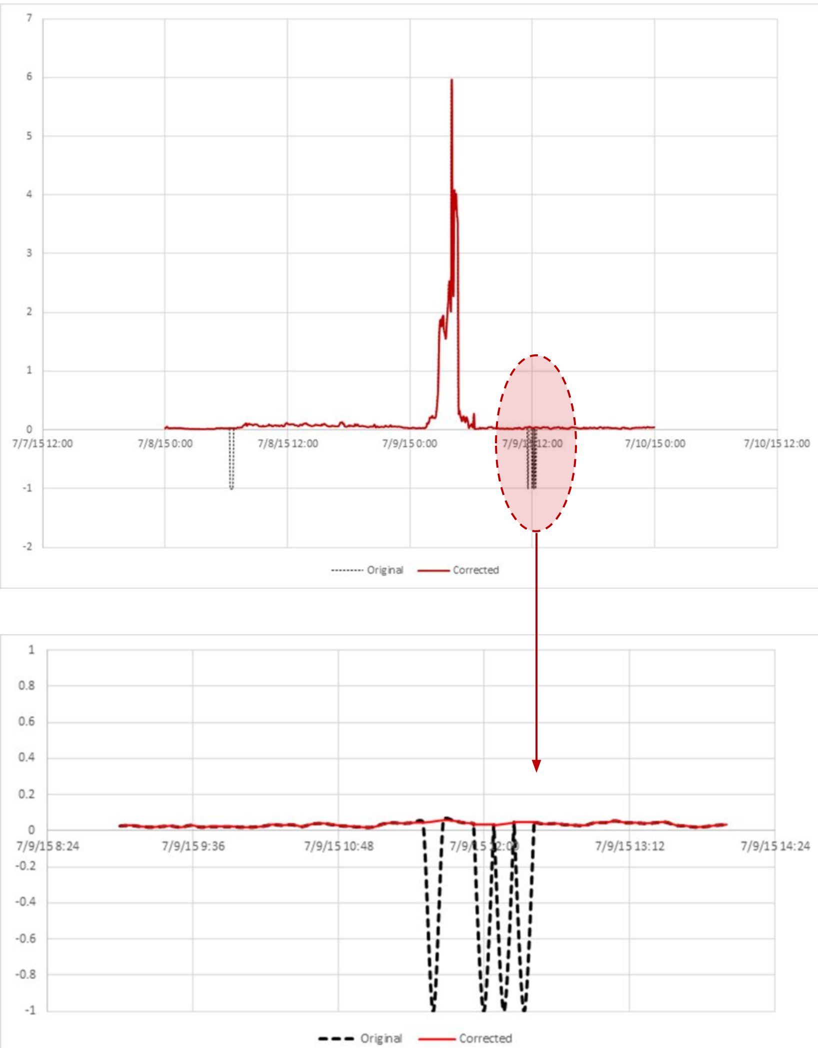
Real Time Modeling starts with Real Time Monitoring



Case Study: South Bend, IN

- 40 sq.miles
- 150 sensors
- Monitor:
  - 36 outfalls,
  - 27 interceptor sites
  - 42 trunkline sites
  - 5 basins

Data QA/QC

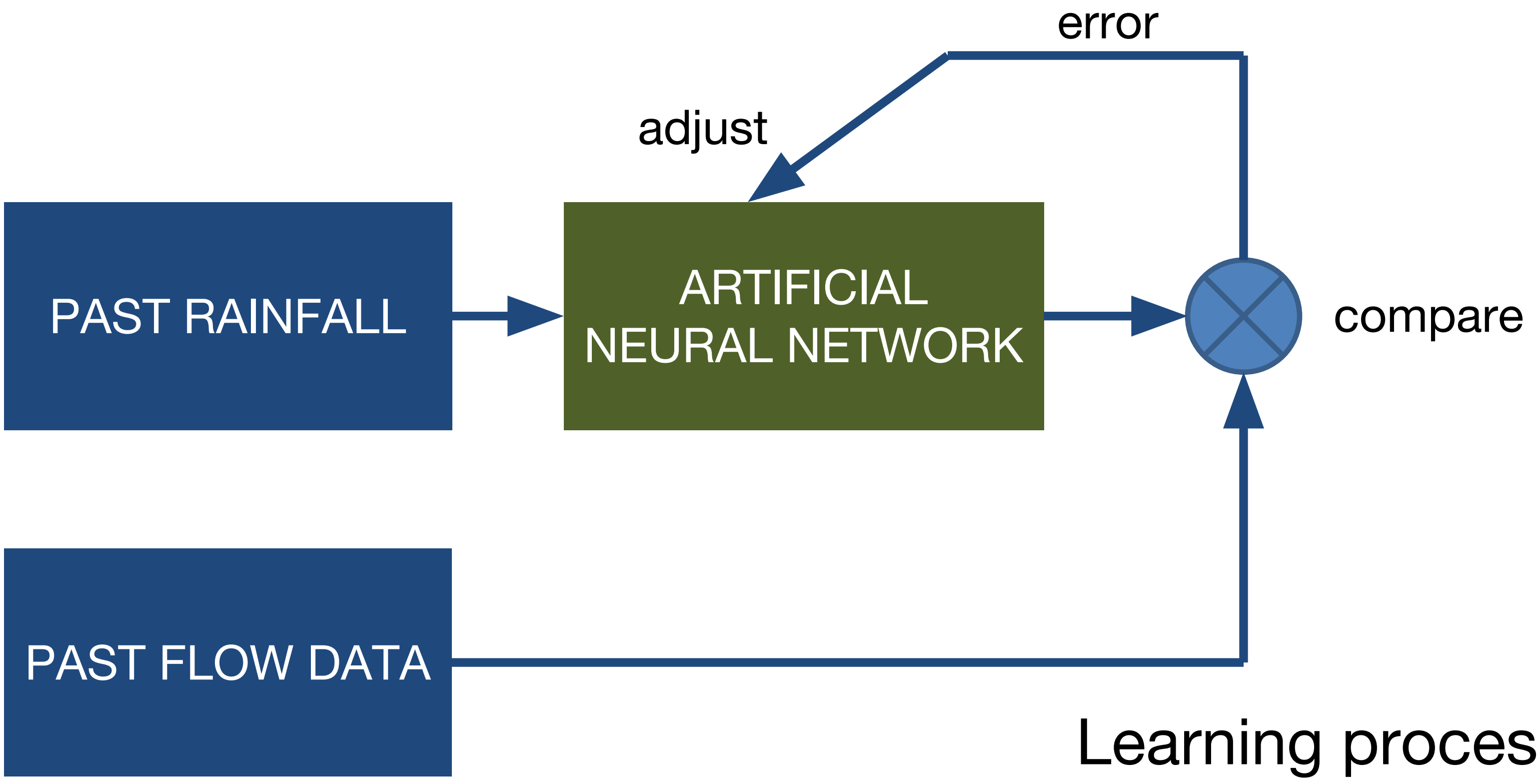


Avoid "garbage in, garbage out"

Eliminate data that has:

- Sensor drifting
- Maintenance/calibration
- Outliers
- Flat lined

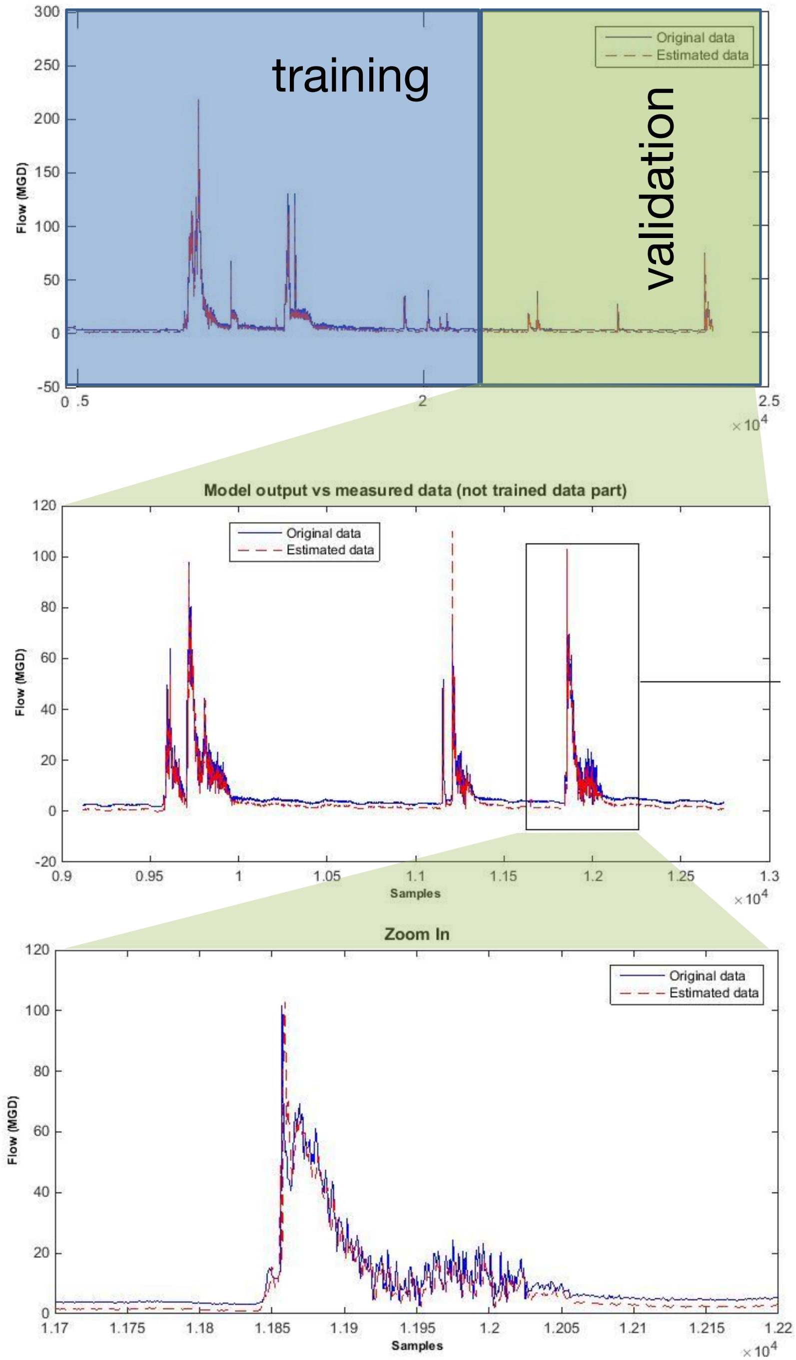
Training Phase



Learning process

- Utilizes historical data
- Data must be diverse
- Data must be related

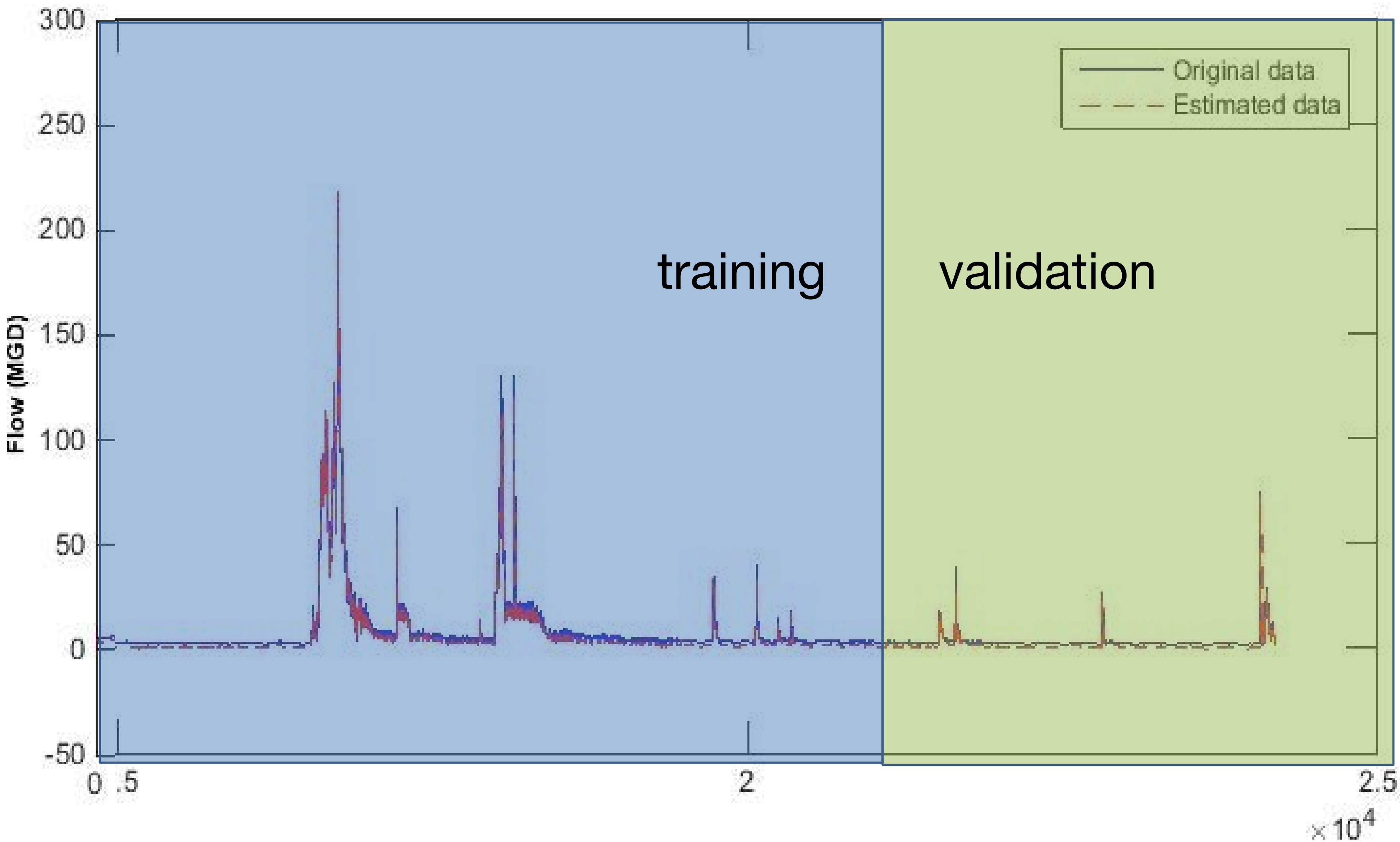
Validation



Ensures that training process was successful:

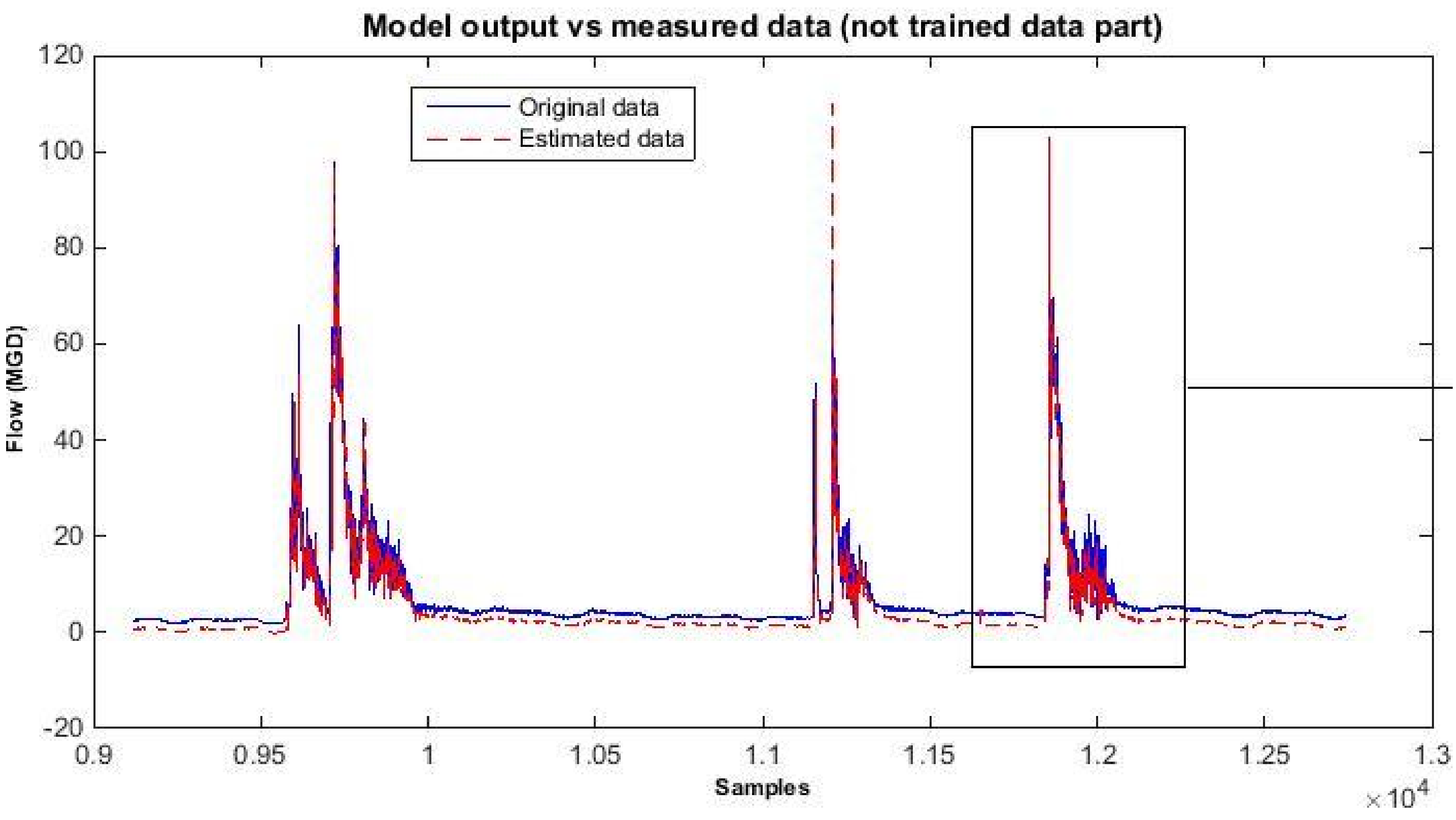
- Utilizes data NOT used for training
- Compares the neural network output data to the measured output
- If validation is unsuccessful repeat training with new/different data

Validation



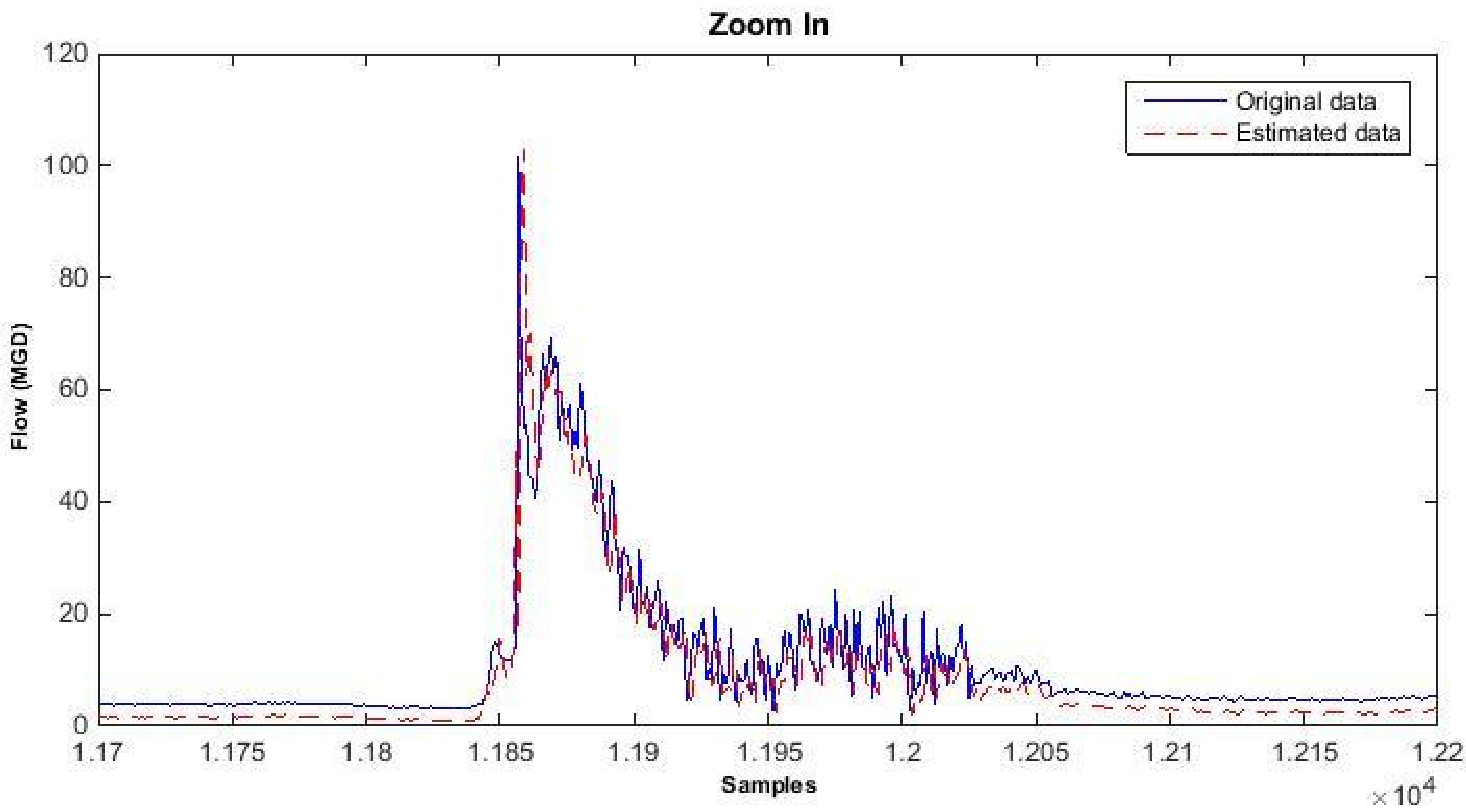
Original data
Estimated data
training
validation
Flow (MGD)
300
250
200
150
100
50
0
-50
0 .5
2
2.5
×10^4

Validation



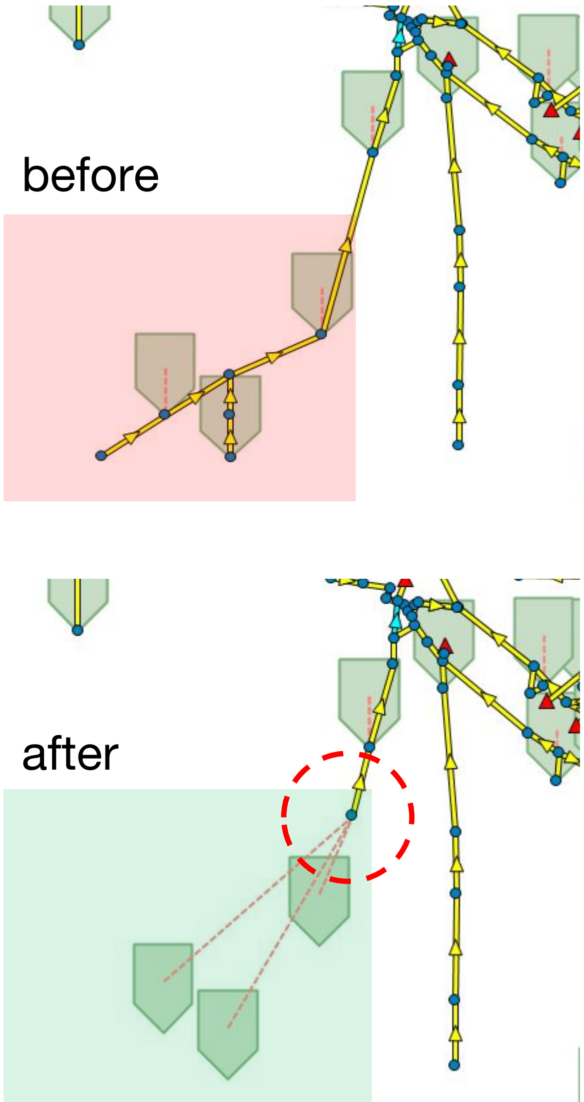
Model output vs measured data (not trained data part)
Original data
Estimated data
Flow (MGD)
Samples
×10^4
120
100
80
60
40
20
0
-20
0.9
0.95
1
1.05
1.1
1.15
1.2
1.25
1.3

Validation



Zoom In
120
100
80
60
40
20
0
Flow (MGD)
Original data
Estimated data
1.17
1.175
1.18
1.185
1.19
1.195
1.2
1.205
1.21
1.215
1.22
Samples
×10^4

Integration with SWMM



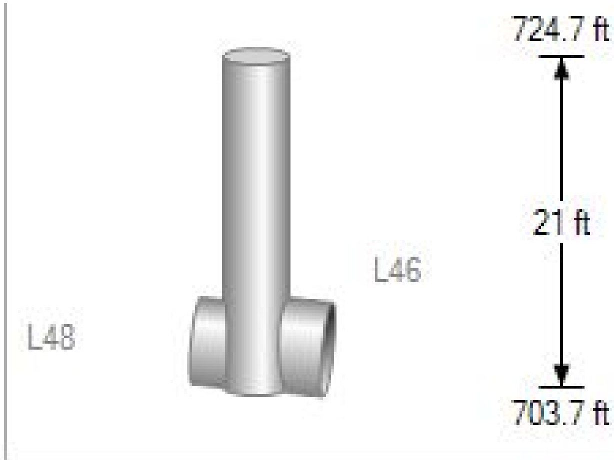
CHRS is mainly used to abstract parts of the model where there is uncertainty:

- runoff dynamics
- upstream sewersheds
- subcatchment

Integrate with SWMM

Maintain downstream pipe network

Integration with SWMM



Junction: 0018C00055_NN

Attributes	
Name	0018C00055_NN
X-Coordinate	171390
Y-Coordinate	2333940

- Works at the node level
- Simulates inflow
- Neural Network description and parameters in external file
- Neural Network is trained in Matlab, parameters transferred to SWMM

018C00055_NN.ENN

```
; For TMP22-2 -- values from  2015-10-12
NN_INPUT_STREAMS 1
NN_INPUT_DELAYS 2
NN_HIDDEN 5              ; N in comments below
NN_OUTPUT 1
NN_INPUT1_MIN_MAX    0     6.8441    ; >> netc.inputs{1}.range
NN_OUTPUT_MIN_MAX    0   129.1570    ; >> netc.outputs{2}.range

NN_HIDDEN_WEIGHTS    ; >> netc.IW{1} for N hidden neurons, connected back to input1(t
```

Result Example

Nash-Sutcliffe 2013 : 0.29
Nash-Sutcliffe 2016 : 0.38
Nash-Sutcliffe CHRS: 0.93

Conclusions

- CHRS can produce operational models that are:
  - fast
  - self learning
  - highly accurate
- Integration with SWMM allows CHRS to leverage pipe network computational engine.
- Release as open source in near future.
- Work is now focused on how to automatically QA/QC sensor data.

Questions?

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