FP7 Collaborative research on flood resilience in urban areas

Machine learning-based Early Warning System for Urban Flood Management

Andrew P. Duncan, Edward C. Keedwell,
Slobodan Djordjević, Dragan A. Savić

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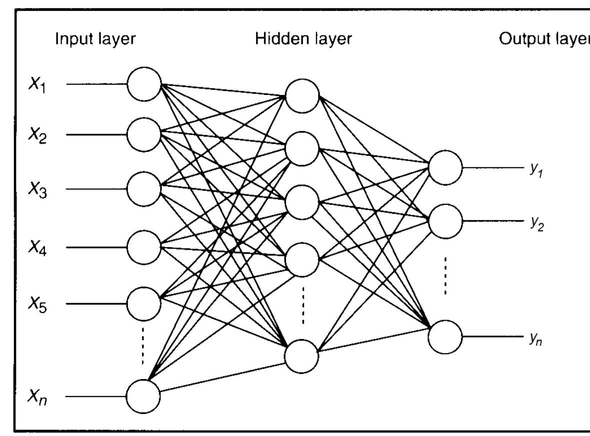
Overview

- **Introduction**
  - Intelligent water networks – “big data”
  - Machine learning models – Artificial Neural Networks (ANN)
  - Application – prediction of urban flooding at multiple nodes
  - Focus on limits of prediction using actual rainfall as input
- **Methodology**
  - Determination of Time of Concentration of each sewer node
  - Optimisation of ANN architecture
  - Predictive timing trial
- **Results**
  - Optimal ANN architecture
  - Timing trial results
- **Conclusions & future work**

Introduction

- **Intelligent water networks – "big data"**
  - **Need for early warning of urban flooding in real-time**
  - **Operationally useful lead times are greater than 2 hours**
  - **What are the predictive limits of data-driven models, based on using actual rainfall as input?**
- **Machine learning models – ANN**
  - **Well-researched and well-documented**
  - **Not yet widely used in water industry**
  - **Most studies use single output node**
    - **Multiple output node approach:**
    - **Sewerage nodes**
    - **Similarities in hydrographs exploited**
  - **Most studies use single timestep advance - prediction**
    - **Multiple timestep advance – characterisation of performance**



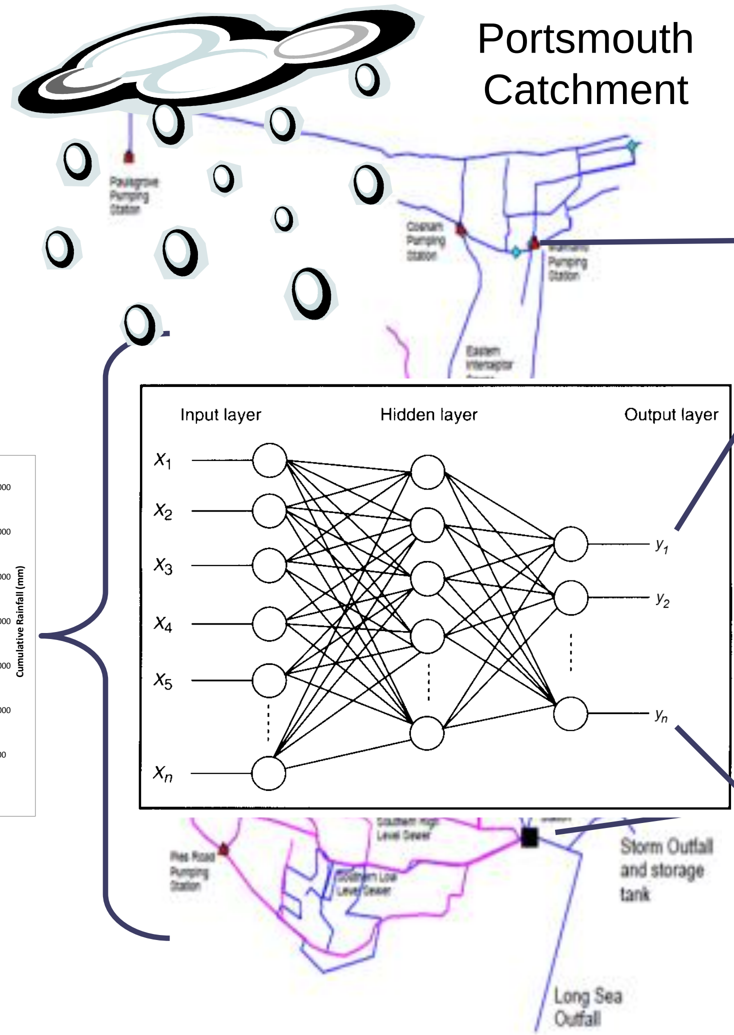
Methodology

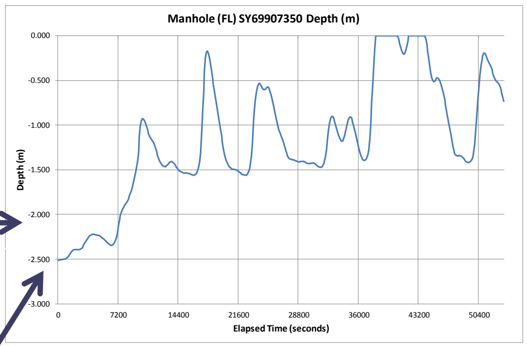
- **Case study – Portsmouth, UK**
  - **Scenario**
  - **Inputs:**
    - **Rainfall intensity**
    - **Cumulative rainfall**
  - **16 design events**
    - **12 training events**
    - **4 test events**
    - **4 durations**
    - **4 return periods**
  - **2-minute timestep**
  - **Outputs:**
    - **10 CSO's**
    - **6 Manholes**
  - **Water level (m)**

Event No	Event Type	Return Period	Duration	Event Use	Event ID
	Design / Real	rrr (Years)	d.dd (Hours)	Trg / Tst	Format rrrddd
1	Design	1	0.5	Trg	001050
2	Design	1	1	Tst	001100
3	Design	1	2	Trg	001200
4	Design	1	4	Trg	001400
5	Design	5	0.5	Trg	005050
6	Design	5	1	Trg	005100
7	Design	5	2	Tst	005200
8	Design	5	4	Trg	005400
9	Design	20	0.5	Trg	020050
10	Design	20	1	Tst	020100
11	Design	20	2	Trg	020200
12	Design	20	4	Trg	020400
13	Design	50	0.5	Trg	050050
14	Design	50	1	Trg	050100
15	Design	50	2	Tst	050200
16	Design	50	4	Trg	050400

Scenario

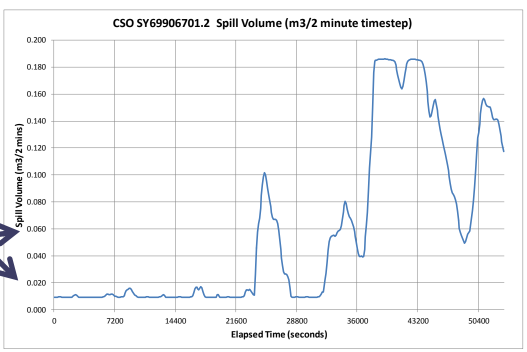
Portsmouth Catchment





Manhole - Water Level Hydrograph

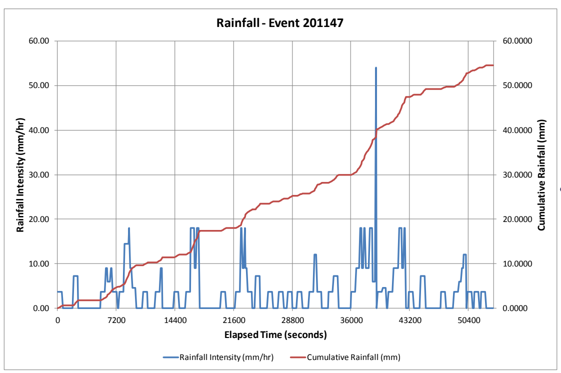
"Targets"



CSO Spill Depth Hydrograph

Rainfall Event –

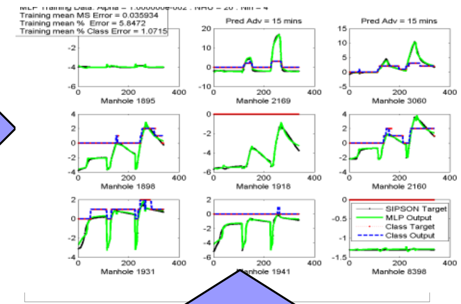
"Inputs"



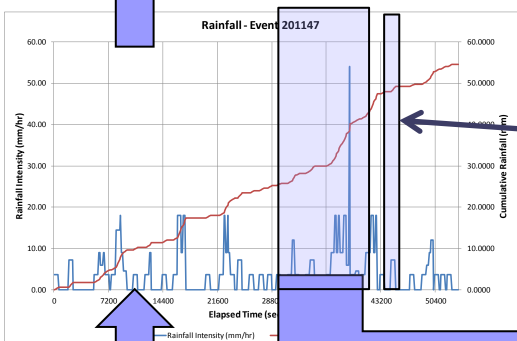
Lagged time window

“Observation data” for several training events

Compare for error metrics

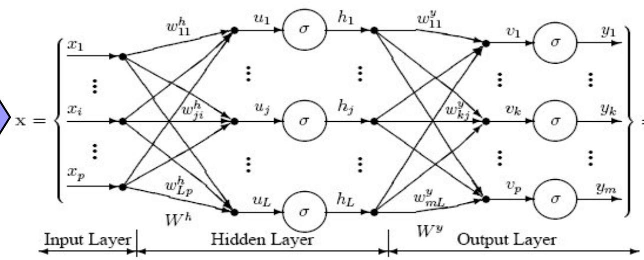


Targets for training



Moving time windows

Rainfall data (design, real, stochastic or spatial)



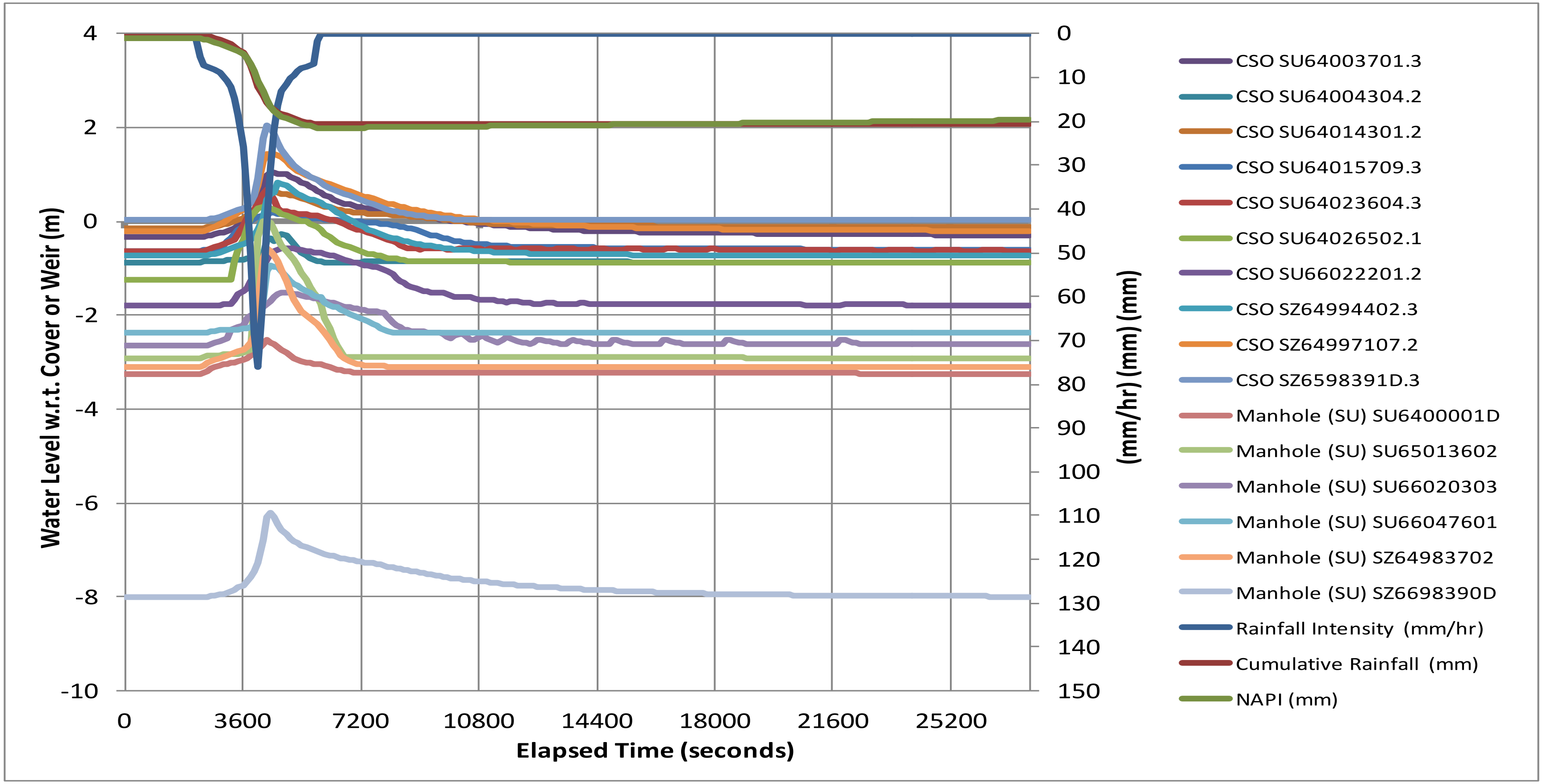
ANN (MATLAB)

Node flood levels, volumes, flow rates, Log bacteria counts

Methodology

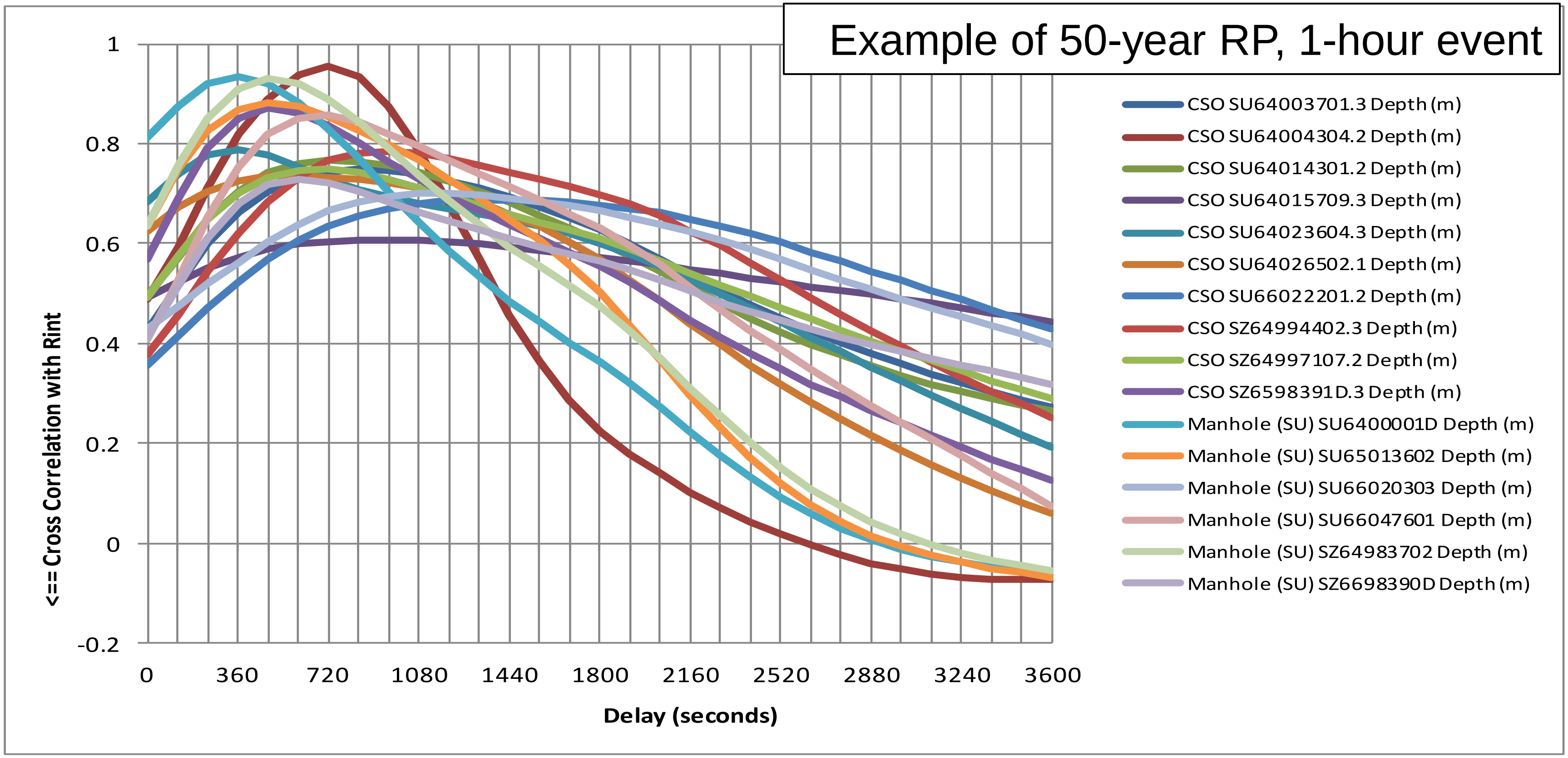
- **Determination of Time of Concentration (ToC)**
  - **of each sewer node**

Example of 50-year RP, 1-hour event



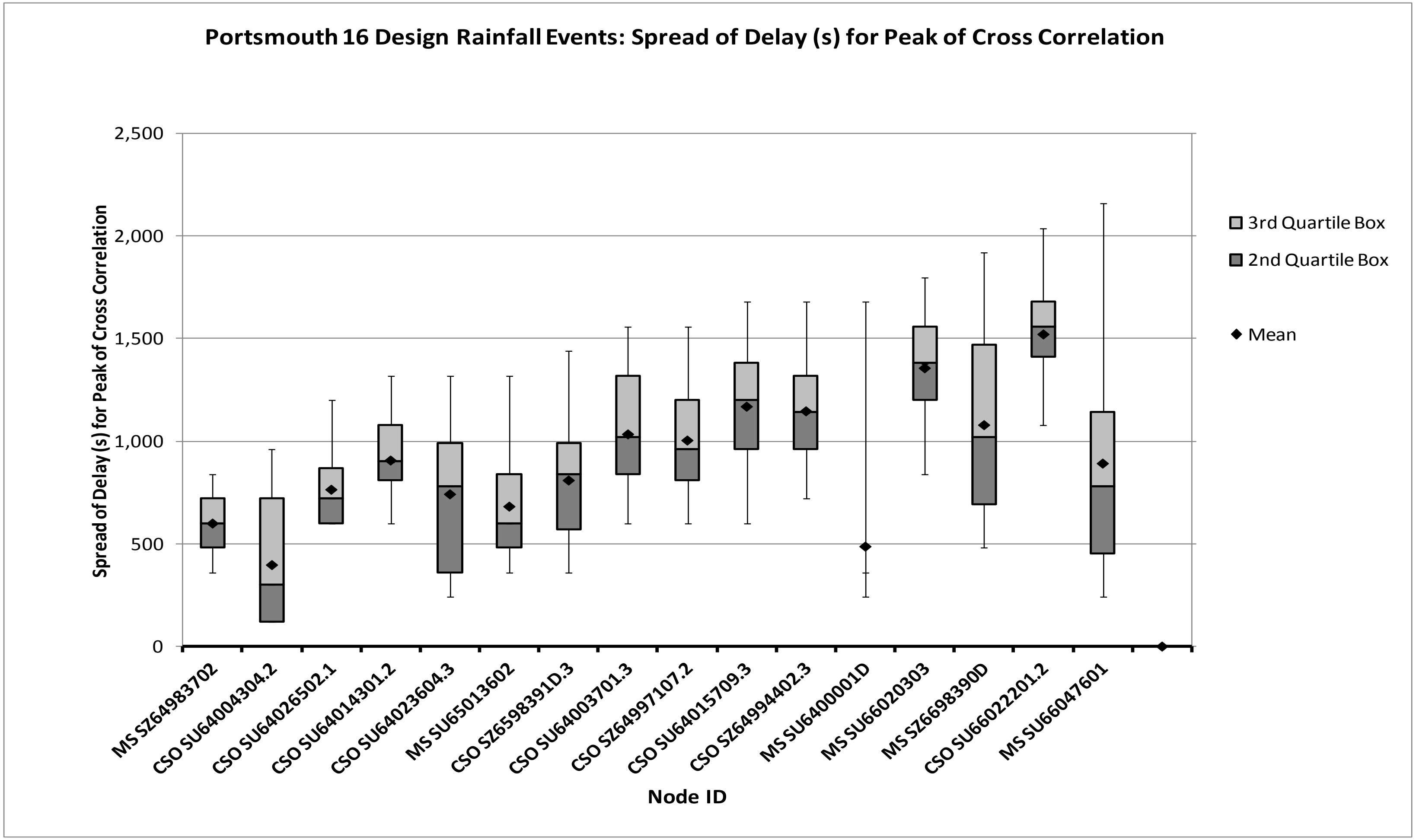
Methodology

- **ToC ≈ Delay of peak of cross-correlation**
  - **Between rainfall intensity (R_{int}) and hydrograph**
  - **for each sewer node and for each event**



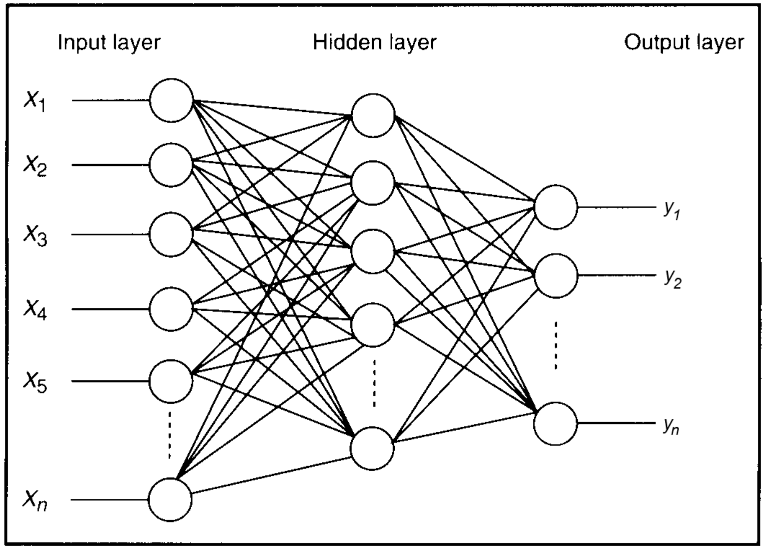
Methodology

- **ToC ≈ Delay of peak of cross-correlation**



Methodology

- **Optimisation of ANN architecture**
- **Controllable features:**
  - **Number of timesteps in moving input time window**
  - **Number of neurons on the hidden layer ("hidden units")**
- **Fixed features:**
  - **Number of output units is fixed by number of sewer nodes being modelled (16)**
  - **All neurons are fully-connected**
  - **Layered architecture**
  - **Feed-forward**
  - **Prediction timestep advance**
    - **1-timestep**
    - **120-seconds**



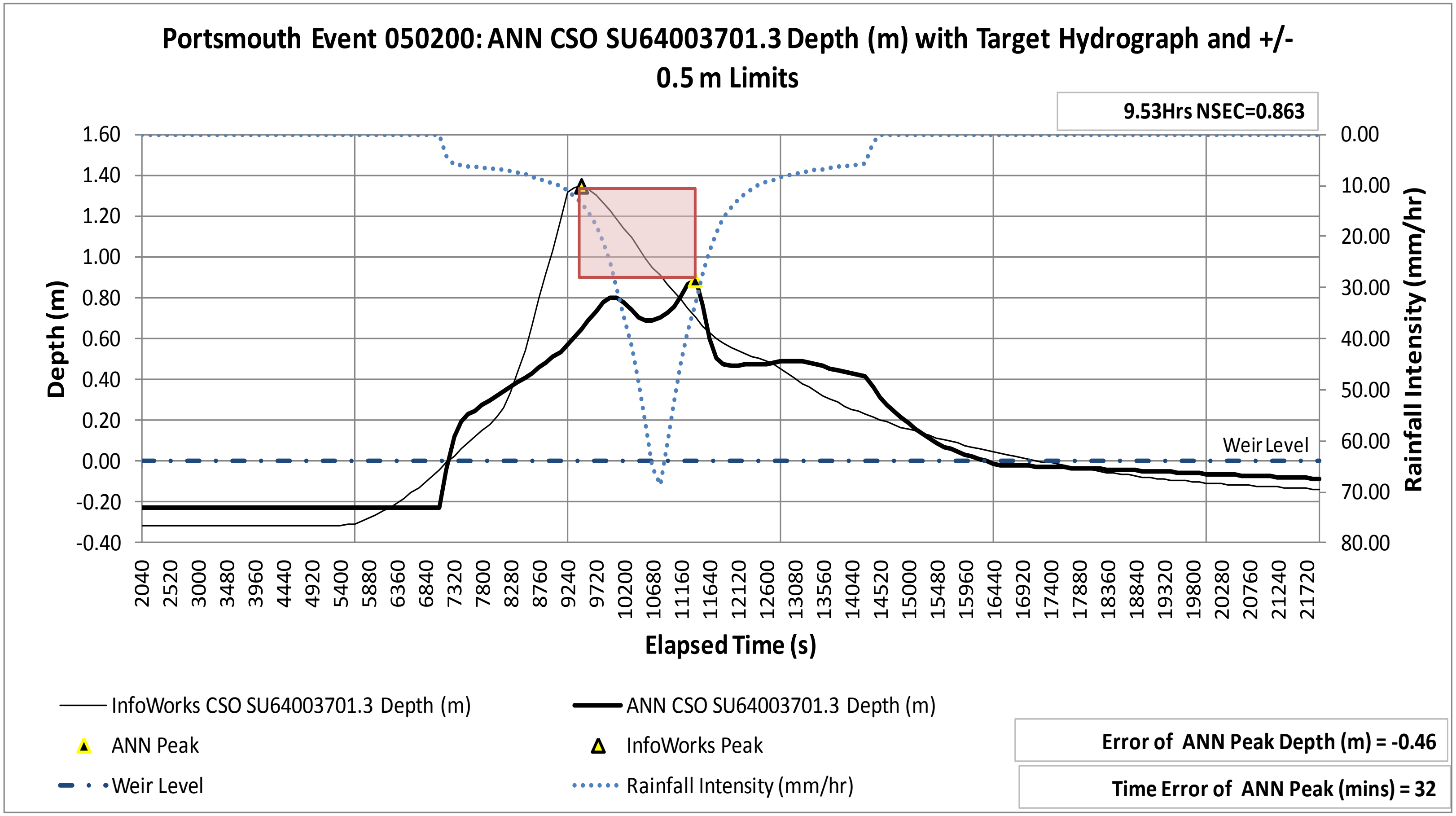
Methodology

- **Predictive timing trial**
- **Controllable feature:**
  - **Number of Prediction Timesteps Advance in output / target time window: "PTA"**
- **Train a different ANN for each PTA**
  - **0 timesteps to 30 timesteps (60-minutes)**
  - **30 timesteps > max ToC for all nodes**
  - **Record 2 metrics for each node**
    - **Nash-Sutcliffe (1970) Efficiency Coefficient**
    - **combined time and amplitude error of the peak of each hydrograph**

$$TA_{err} = (t_t - t_m) * (d_t - d_m)$$

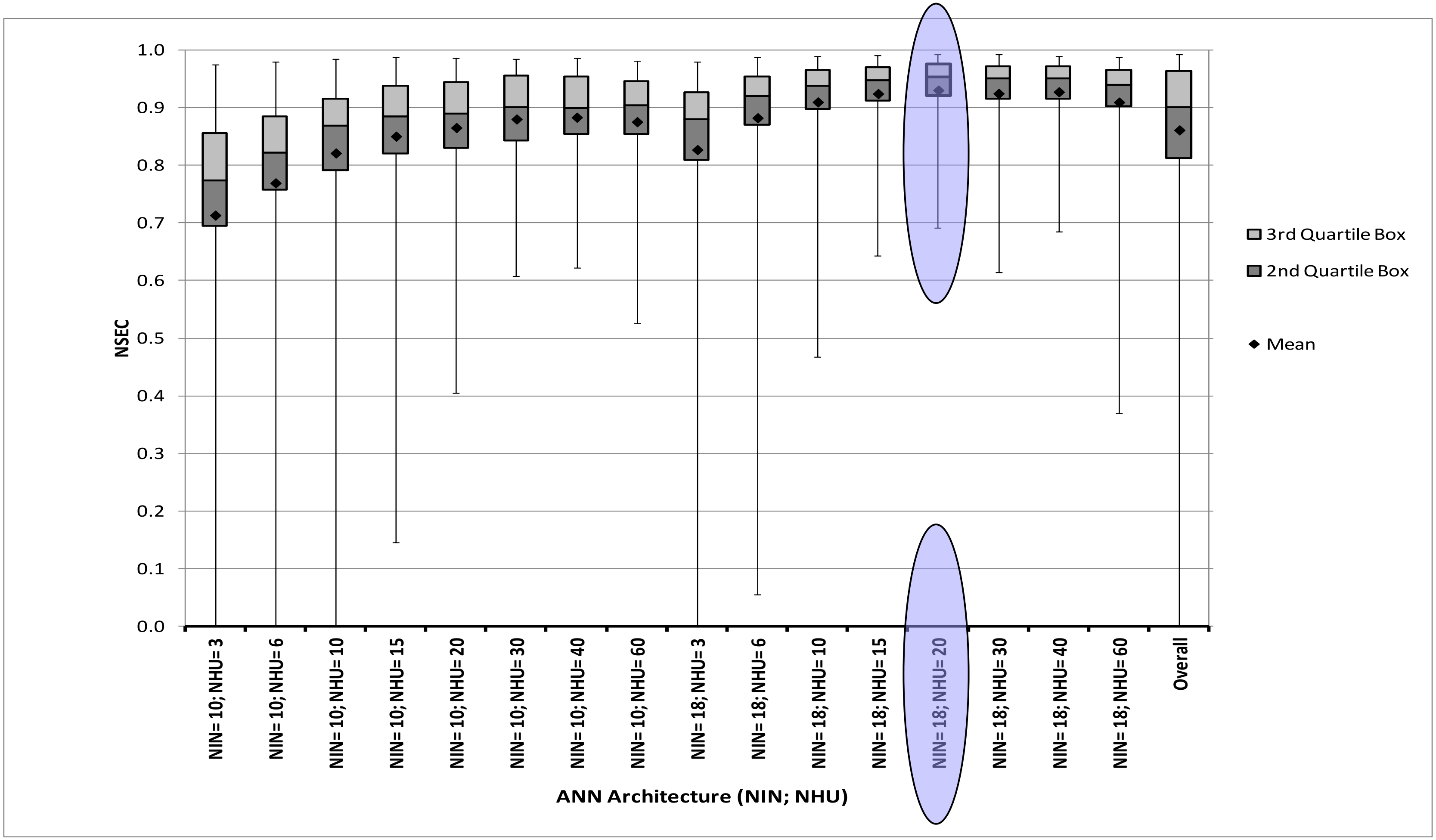
Methodology

- **Predictive timing trial** $$TA_{err} = (t_t - t_m) * (d_t - d_m)$$



Results

- **Optimal ANN architecture**



Results

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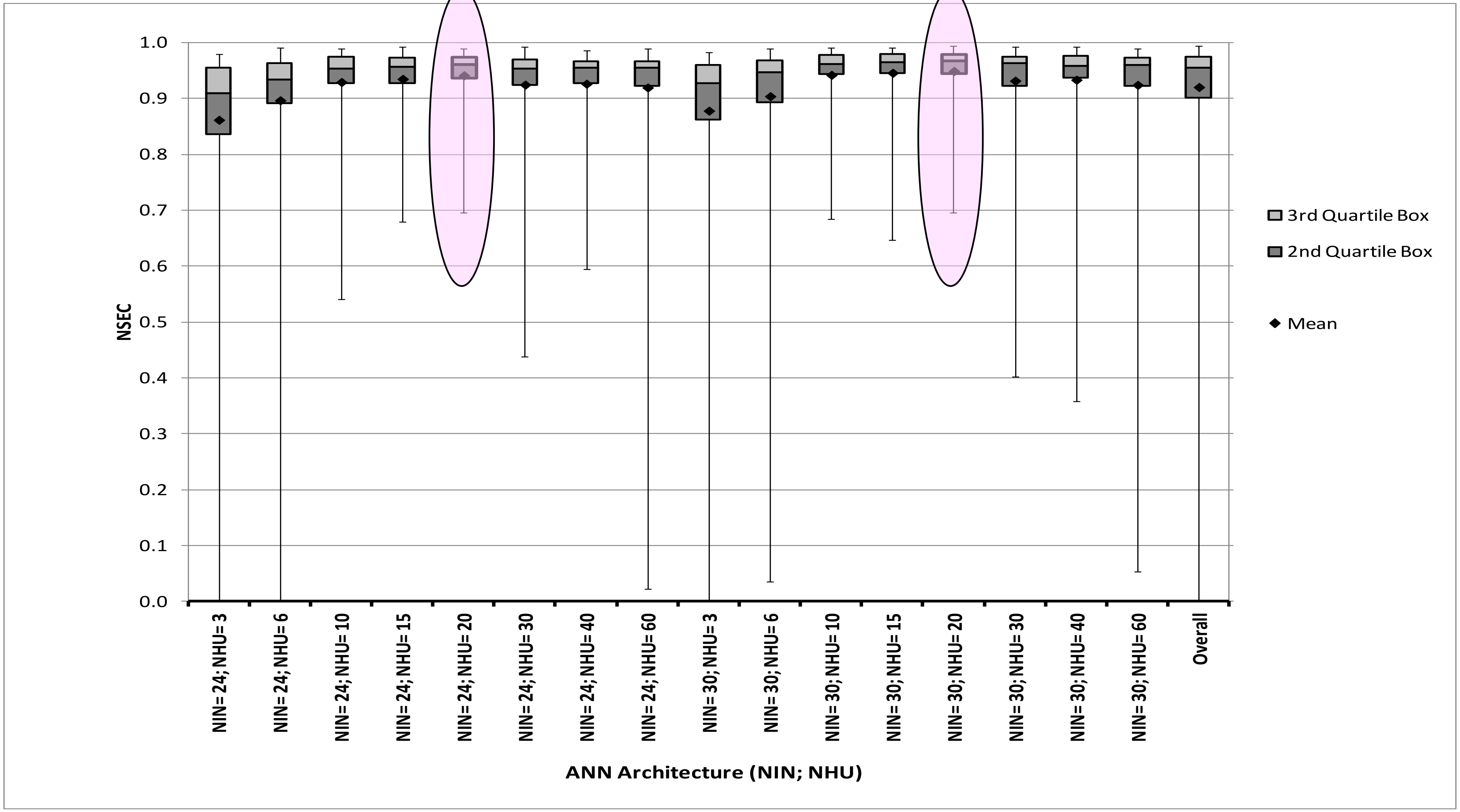
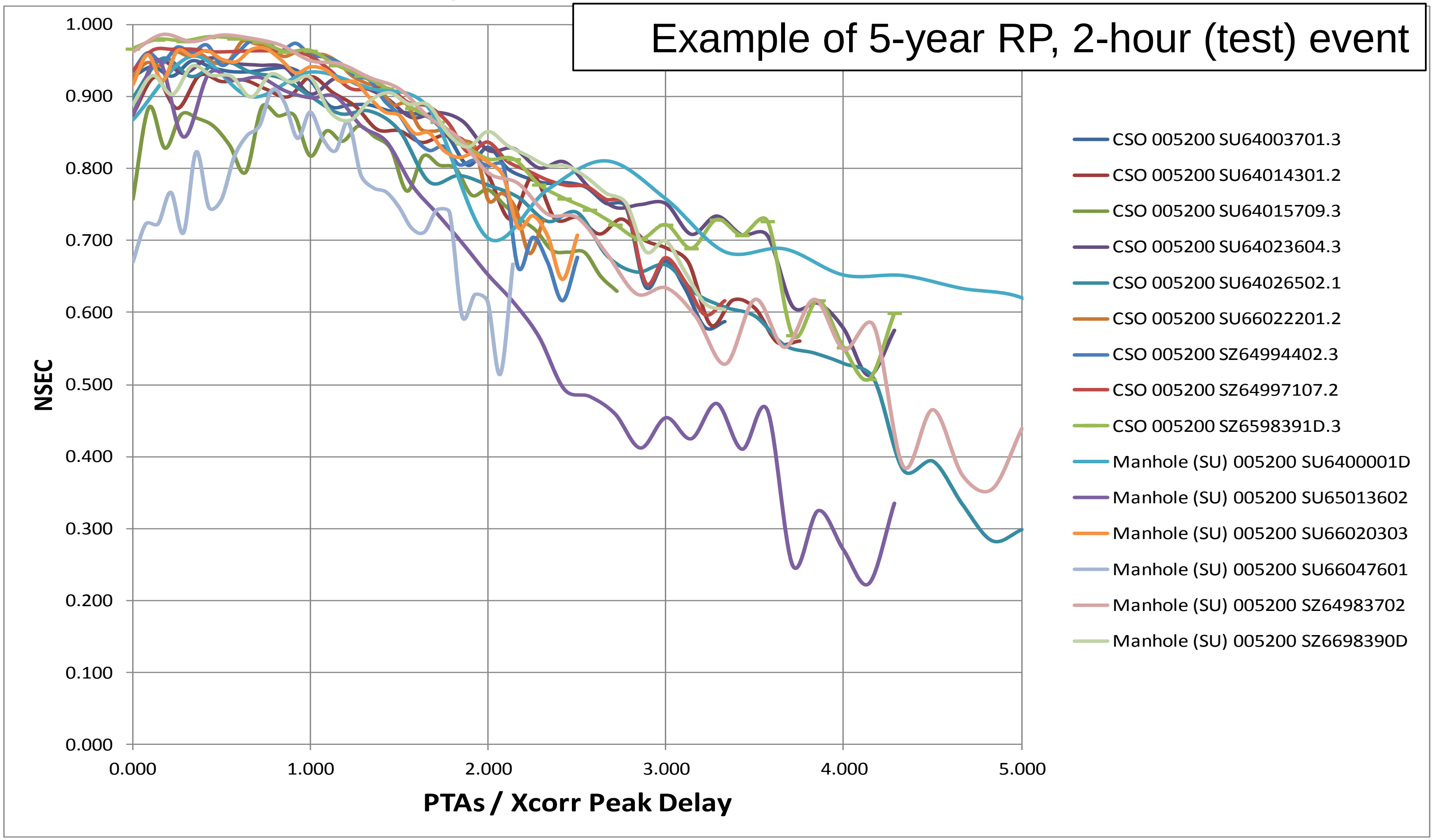


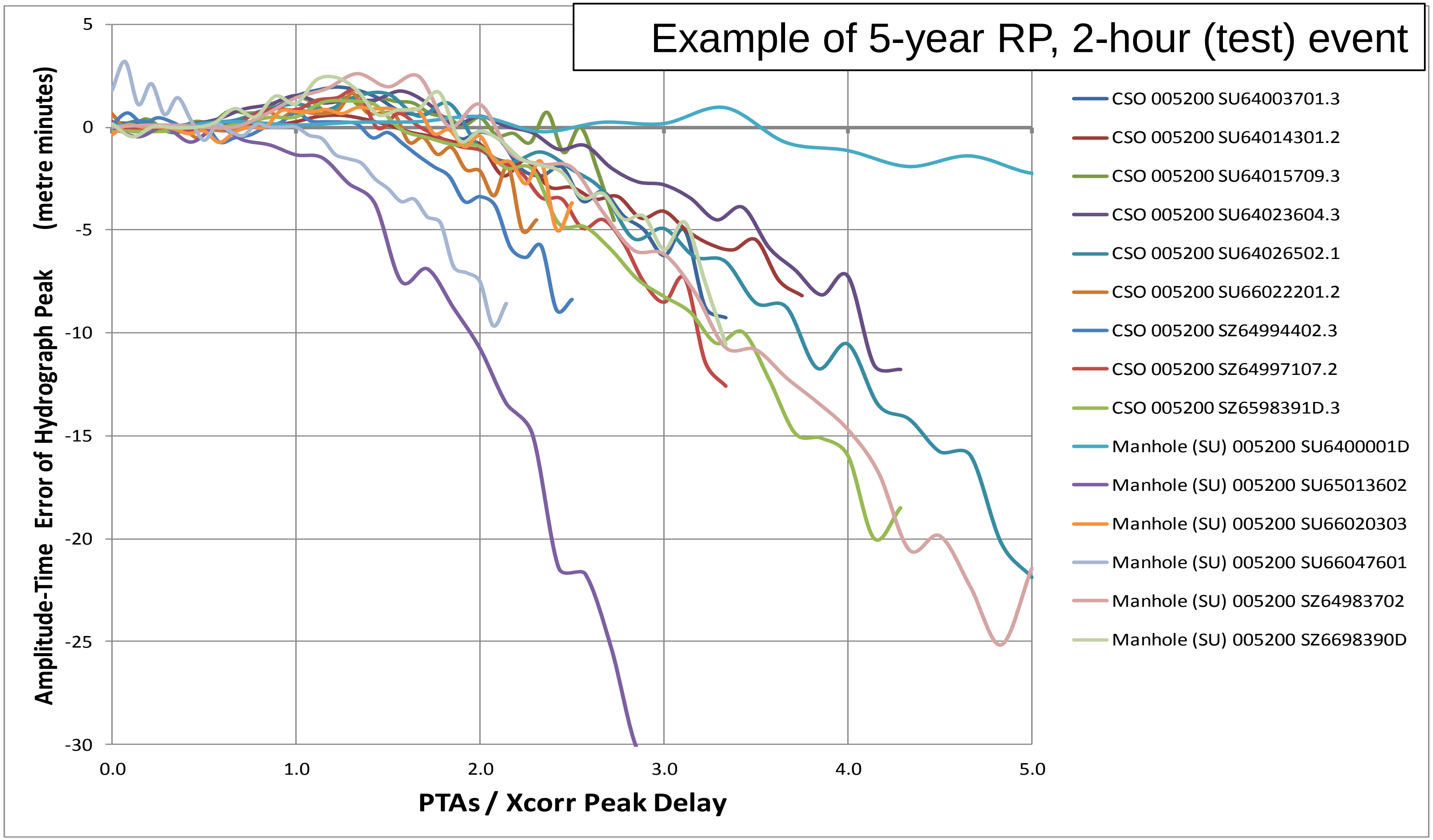
Results

- **Predictive timing trial – NSEC vs ToC**



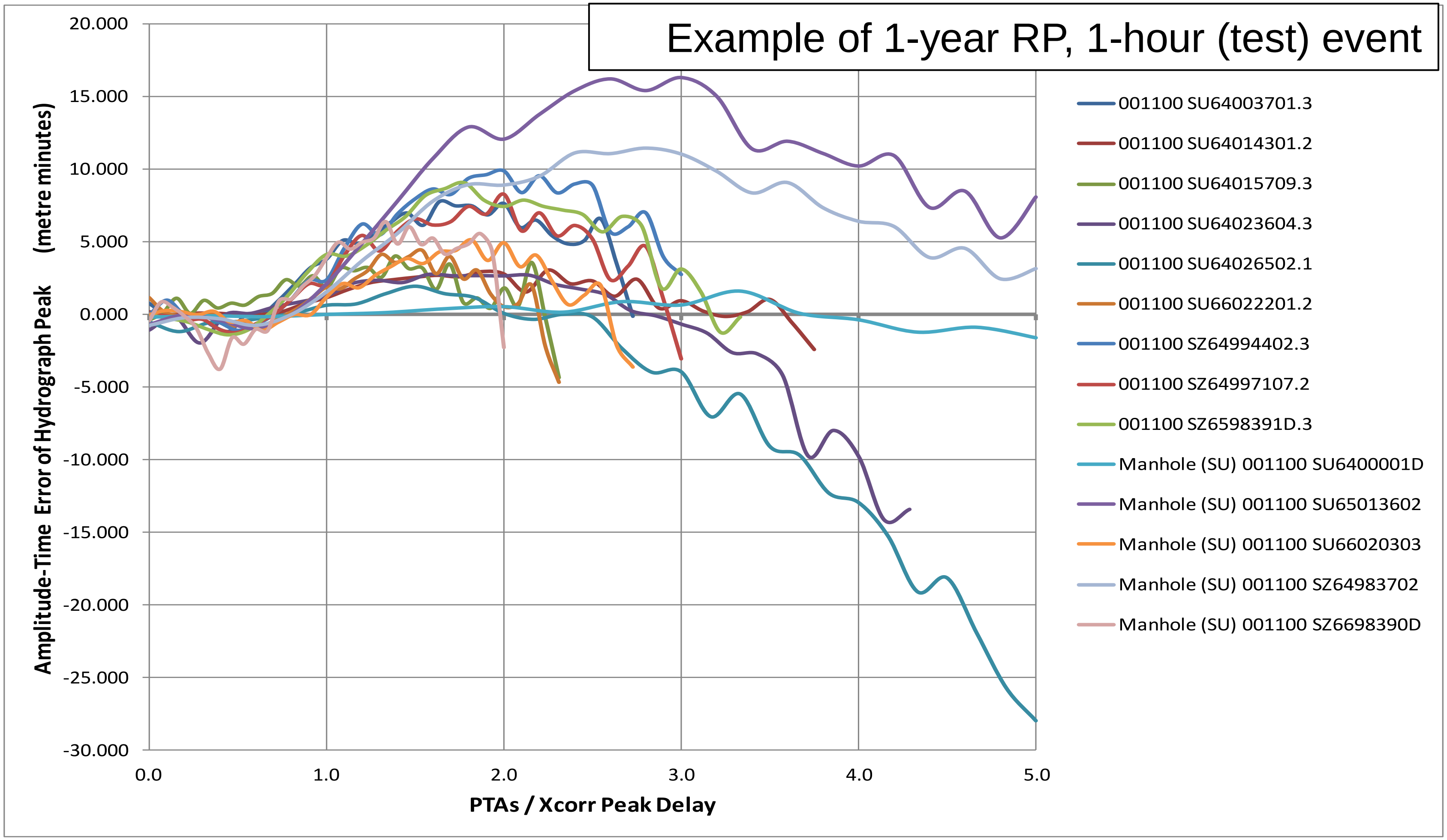
Results

- **Predictive timing trial – TA_{err} vs ToC**



Results

- **Predictive timing trial – TA_{err} vs ToC**



Conclusions & Future Work

- **Multi-node ANNs can produce acceptable performance for urban flood prediction**
  - **Able to exploit similarities in hydrograph shapes**
  - **Small numbers of hidden units (20) were found to be adequate**
  - **Able to accommodate a range of ToC's for nodes**
- **Timing trial shows predictive advance is limited to ToC for each node**
  - **Physical explanation: ToC is the length of time it takes for rainfall on the furthest (upstream) part of the catchment to arrive at the node**
  - **No relevant input signals beyond this level of prediction advance**
- **Operationally useful urban flood forecasts will require rainfall prediction**
  - **Machine learning approaches to nowcasting?**
- **Use of metrics for training ANN – based on focus on flood peak performance**
  - **May yield better results?**

Thanks!

Questions?

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