Urban flood prediction using fuzzy neural networks: An investigation on automated network architecture

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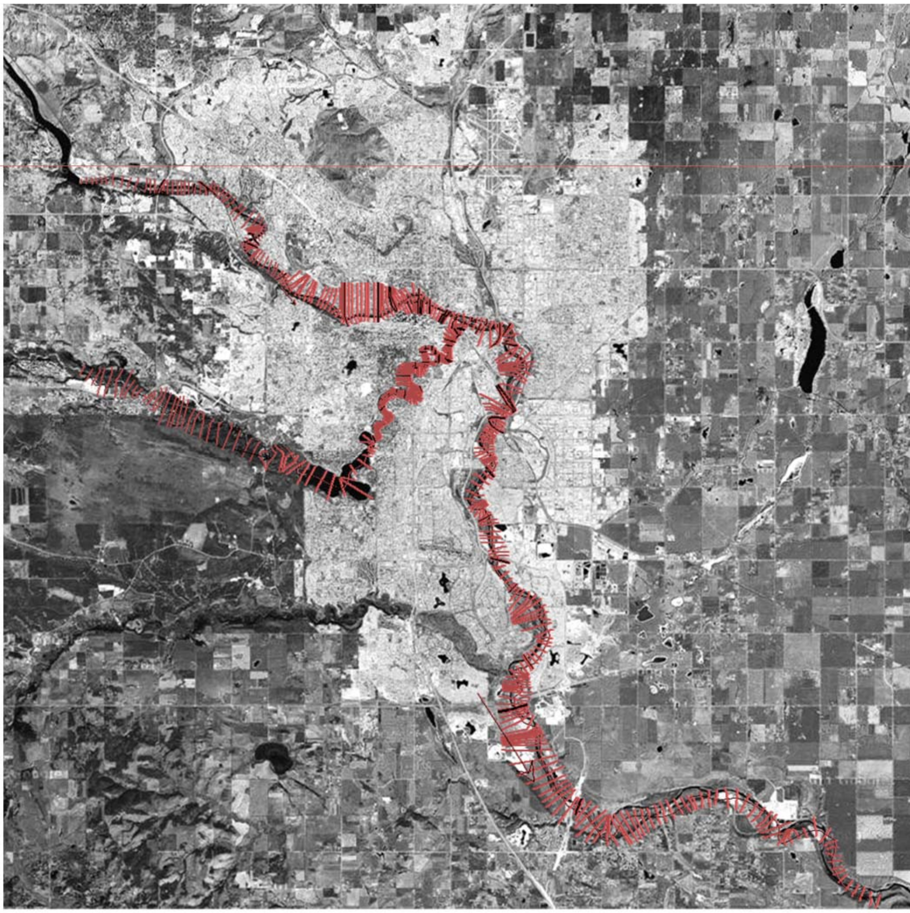
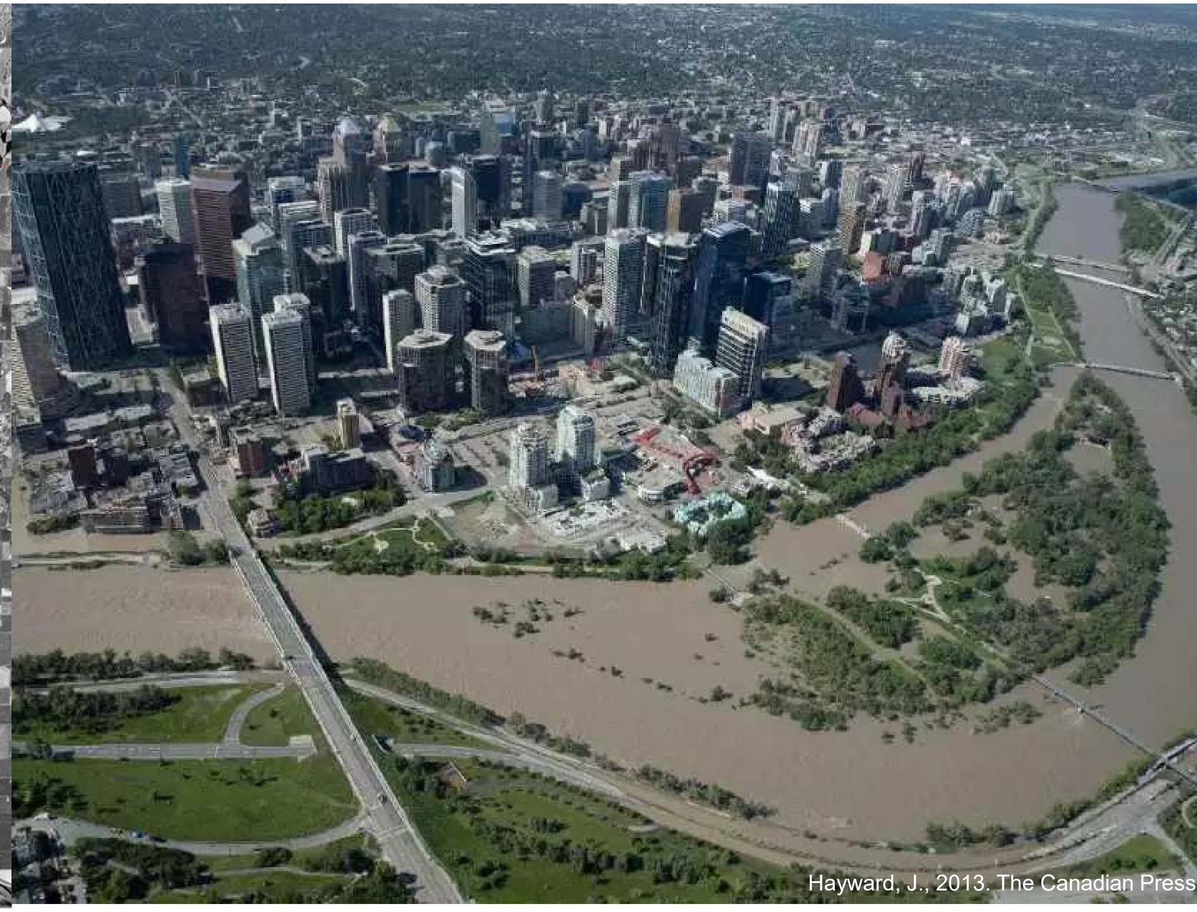
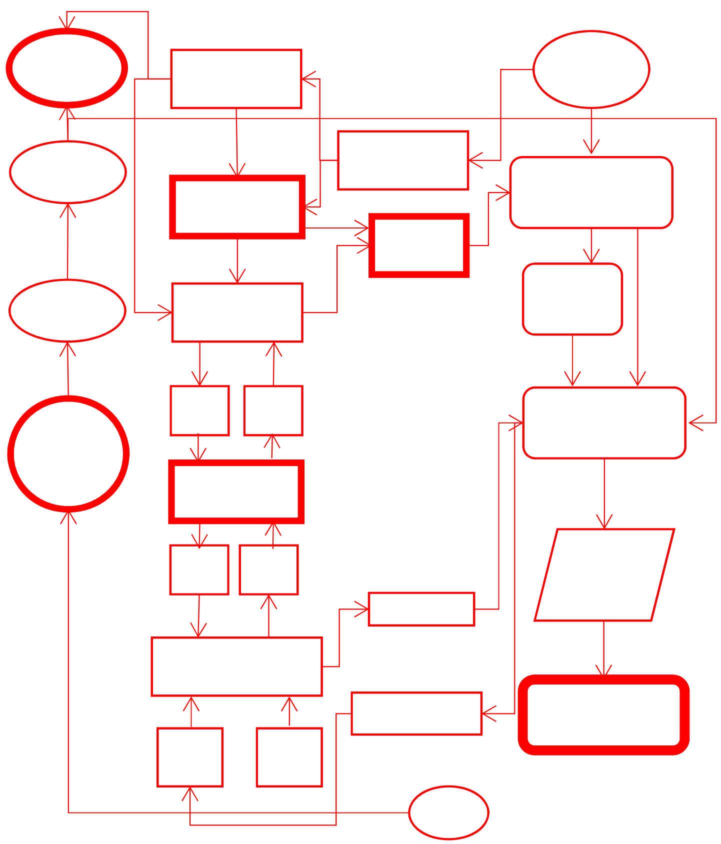



Hayward, J., 2013. The Canadian Press

Physical *v* data-driven models



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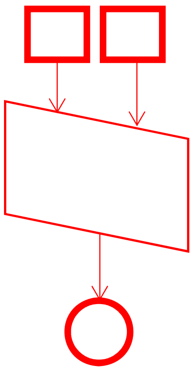
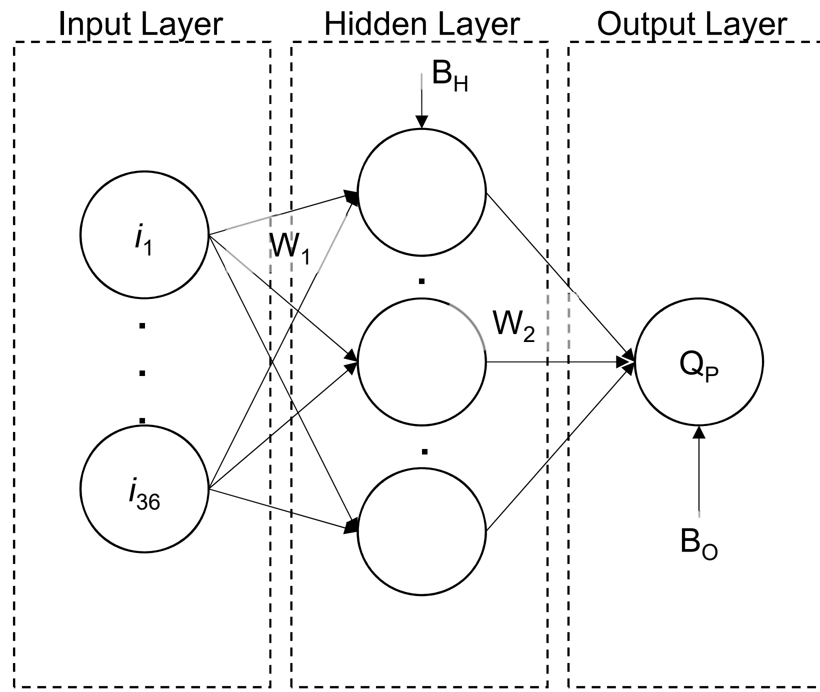
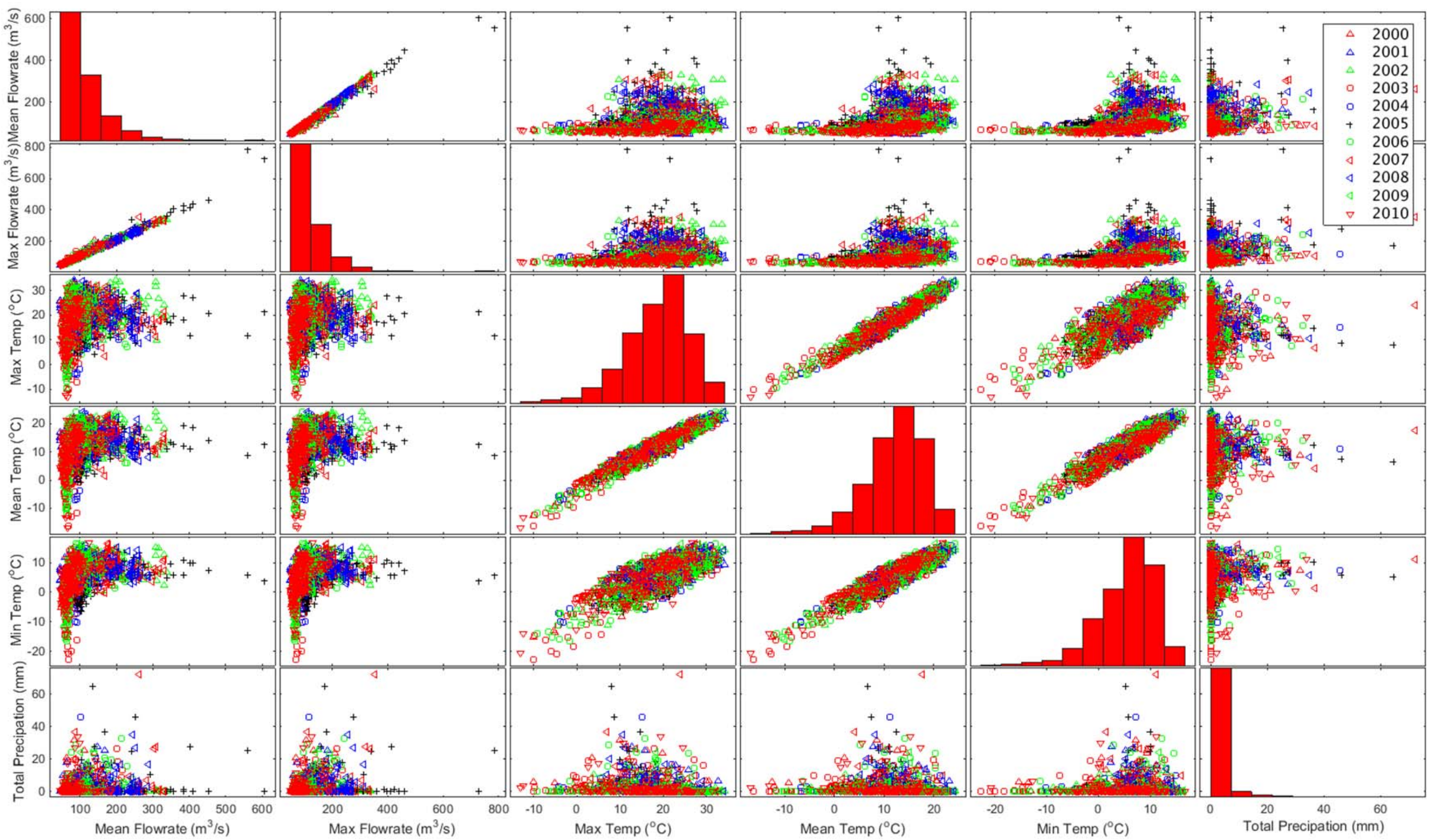


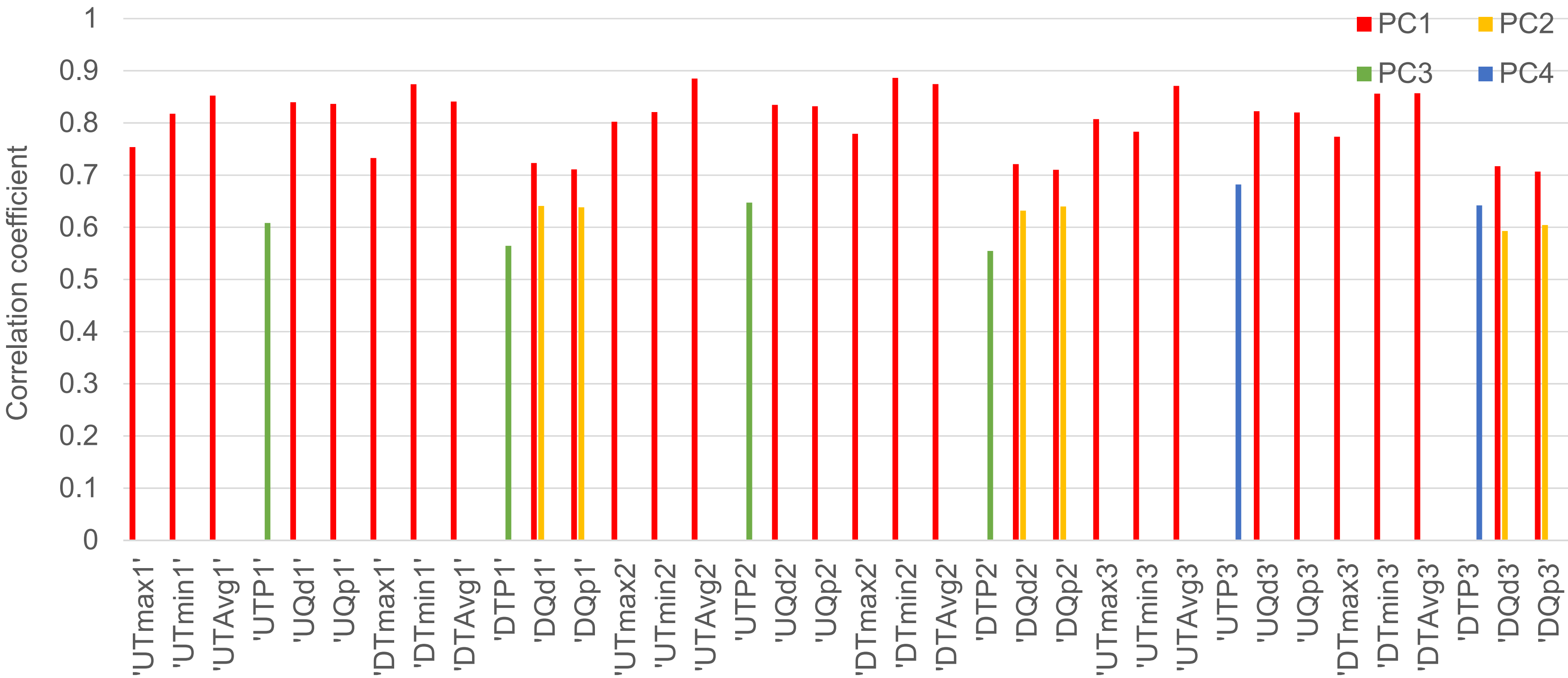
Model architecture

1. Input selection?
   - Compare 3 input variable selection (IVS) methods: PCA, PMI & CNPSA
2. Model structure?
   - Search algorithm for optimum structure
3. Model parameters and output?
   - Fuzzy neural network with fuzzy parameters
4. Others?
   - Training methods & criteria, complexity…



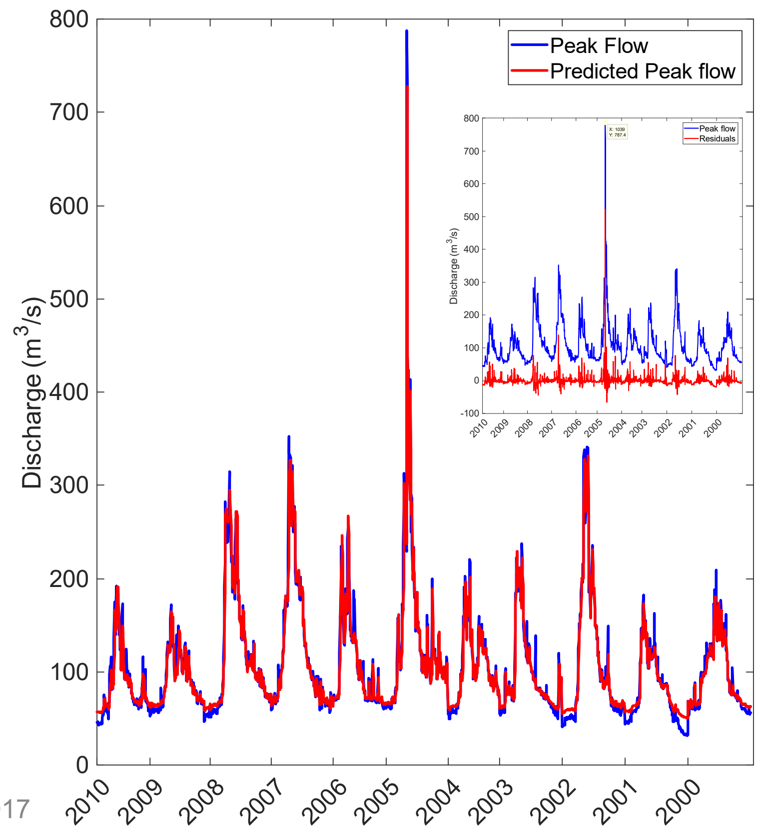

Mean Flowrate (m^3/s)
Max Flowrate (m^3/s)
Max Temp (°C)
Mean Temp (°C)
Min Temp (°C)
Total Precipation (mm)
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

Principal Component Analysis

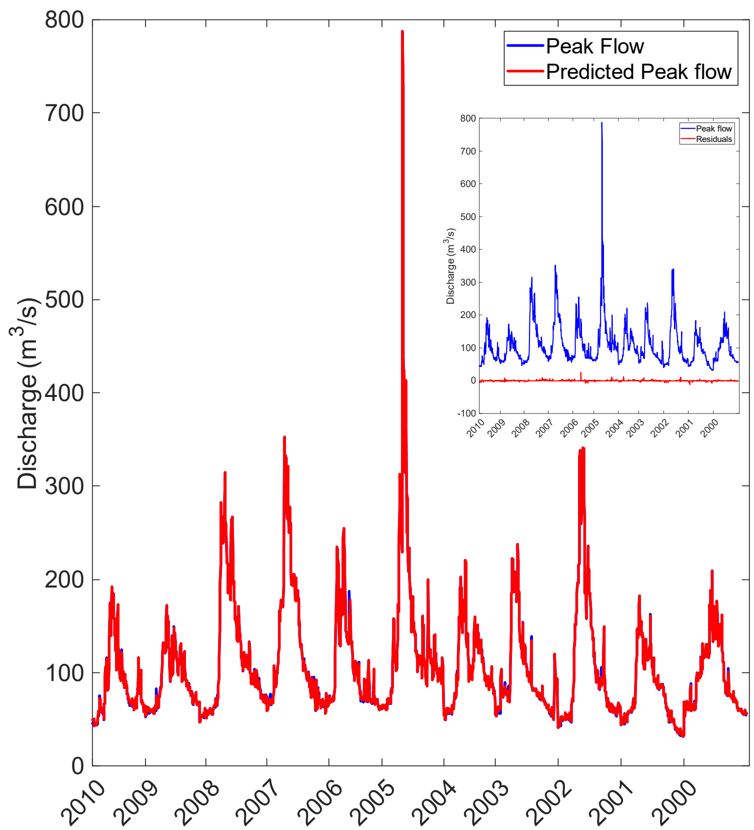


Partial Mutual Information

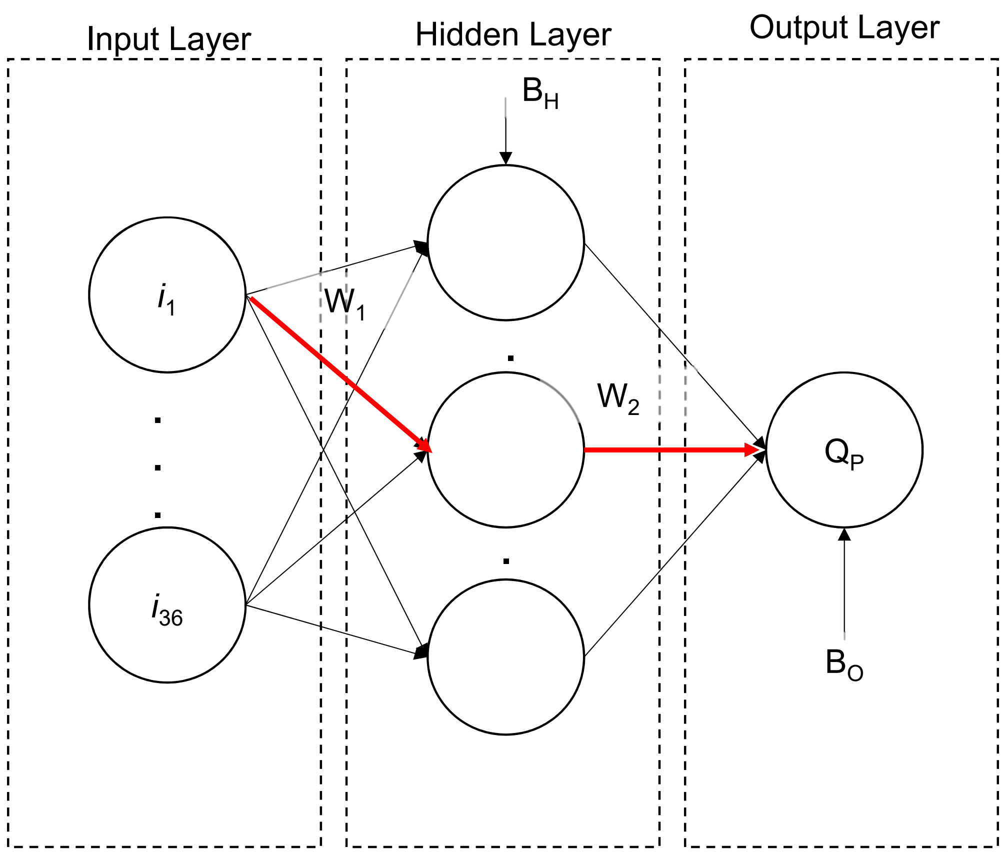
1 variable



22 variables



Combined Neural Pathway Strength Analysis



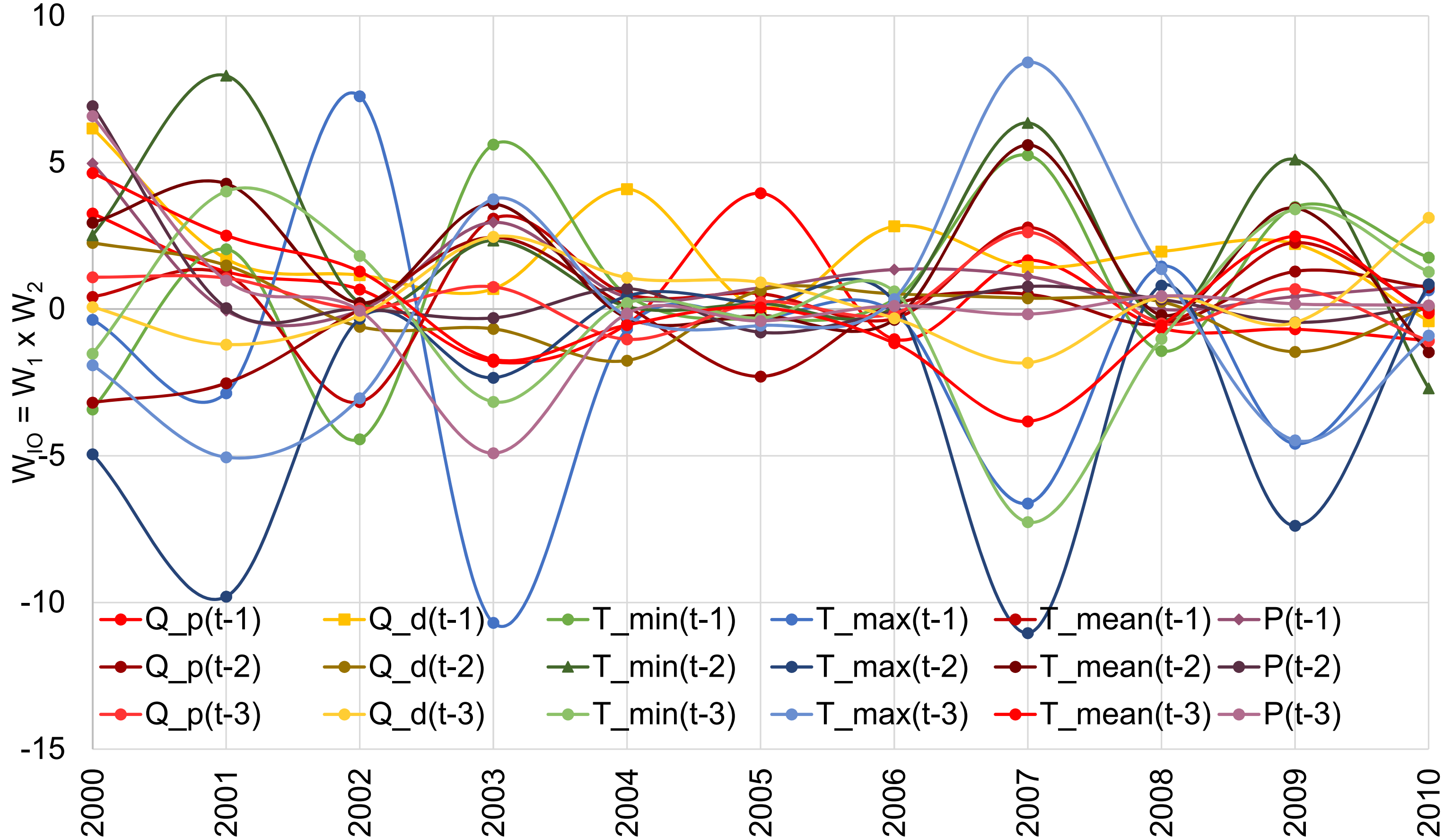
Combined Neural Pathway Strength Analysis

The strength of a pathway from the input to output:

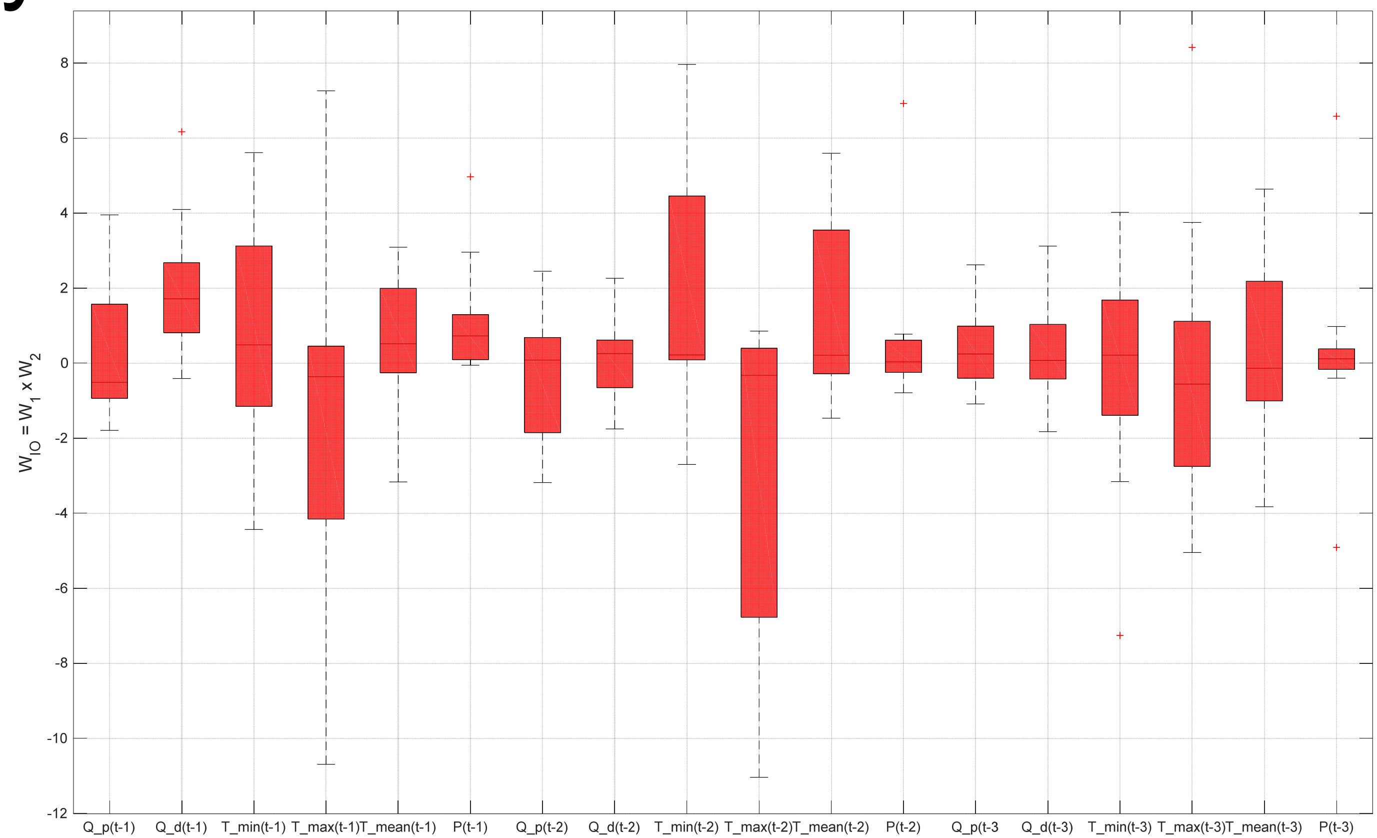
$$W_{IO} = W_1 \times W_2$$

- 36 different W_{IO} values for each year
- The larger the value of the W_{IO} the more influential the input

Combined Neural Pathway Strength Analysis



Combined Neural Pathway Strength Analysis



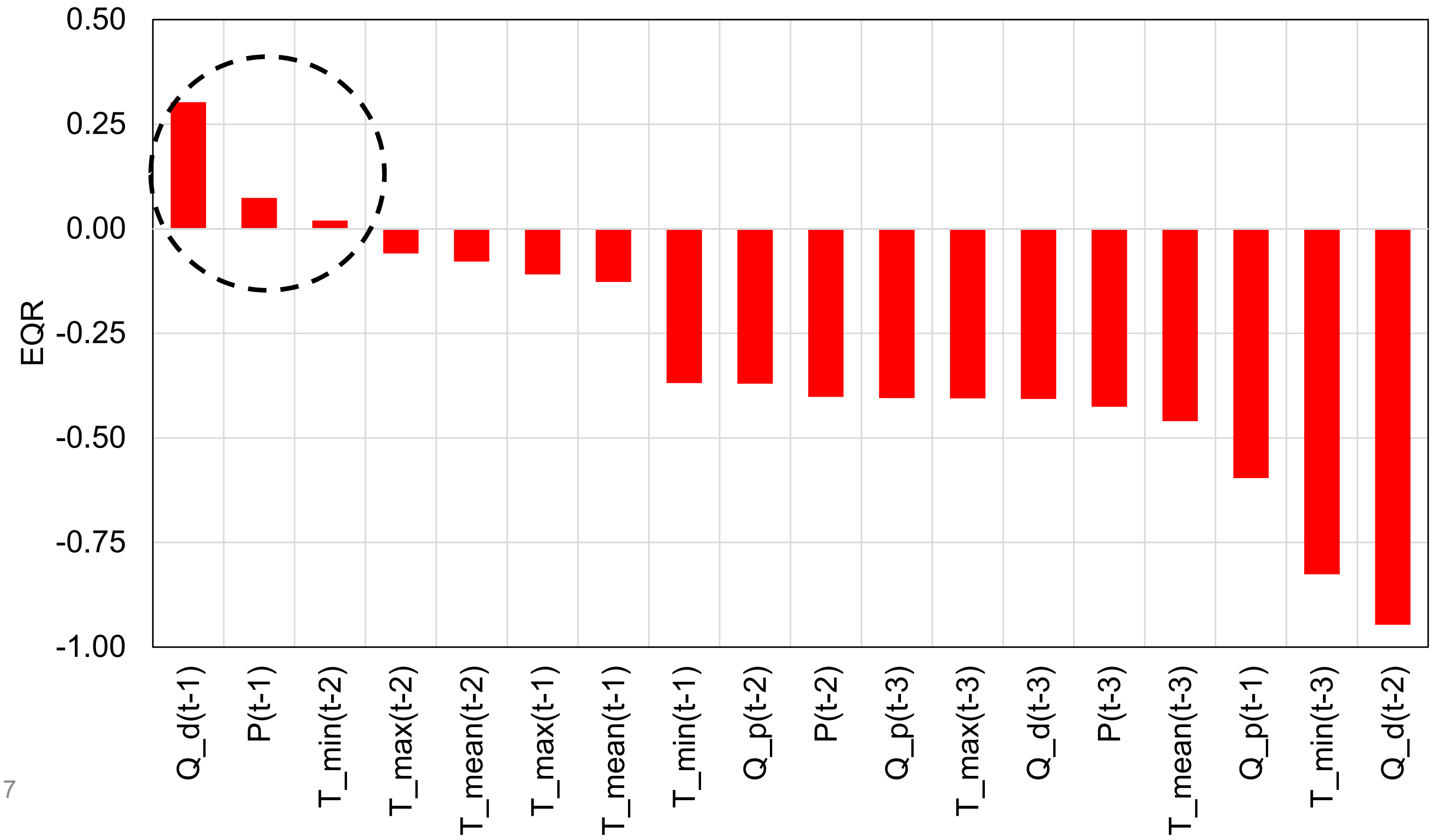
Combined Neural Pathway Strength Analysis

The ensemble interquartile range (EQR):

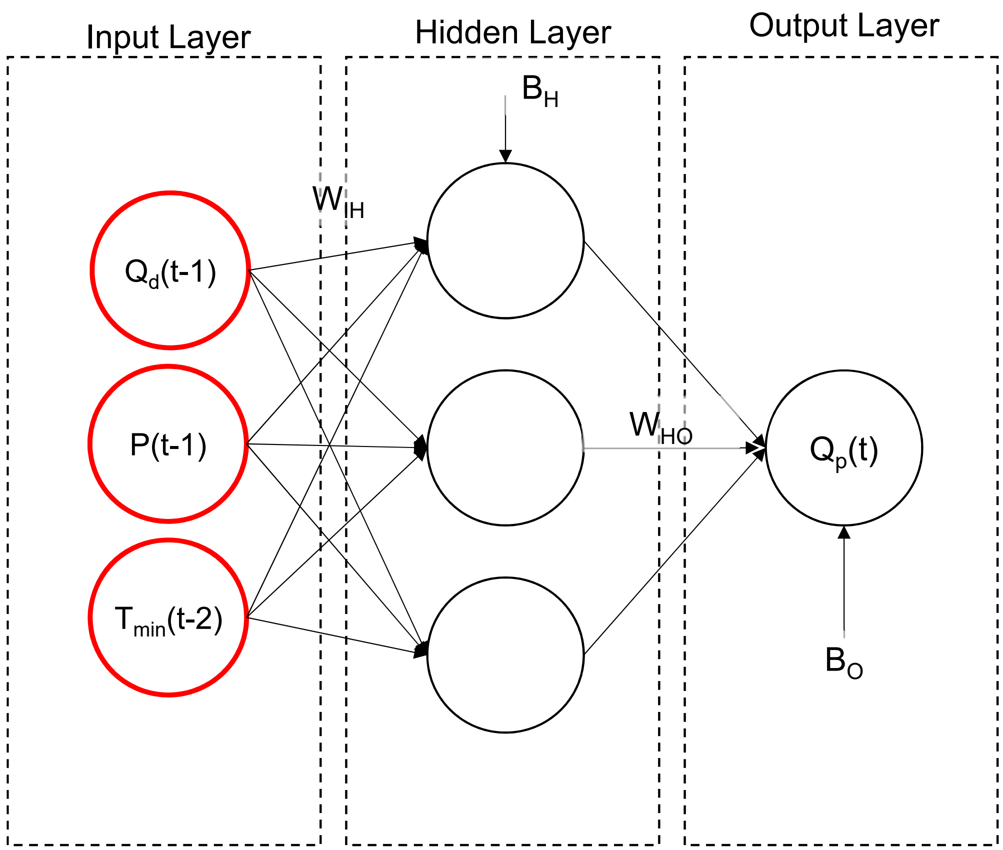
$$EQR = \{\min(|Q_1|,|Q_3|)/\max(|Q_1|,|Q_3|)\}.\mathrm{sgn}(Q_1).\mathrm{sgn}(Q_3)$$

where Q_1 & Q_3 are the first & third quartile of all W_{IO} for each input

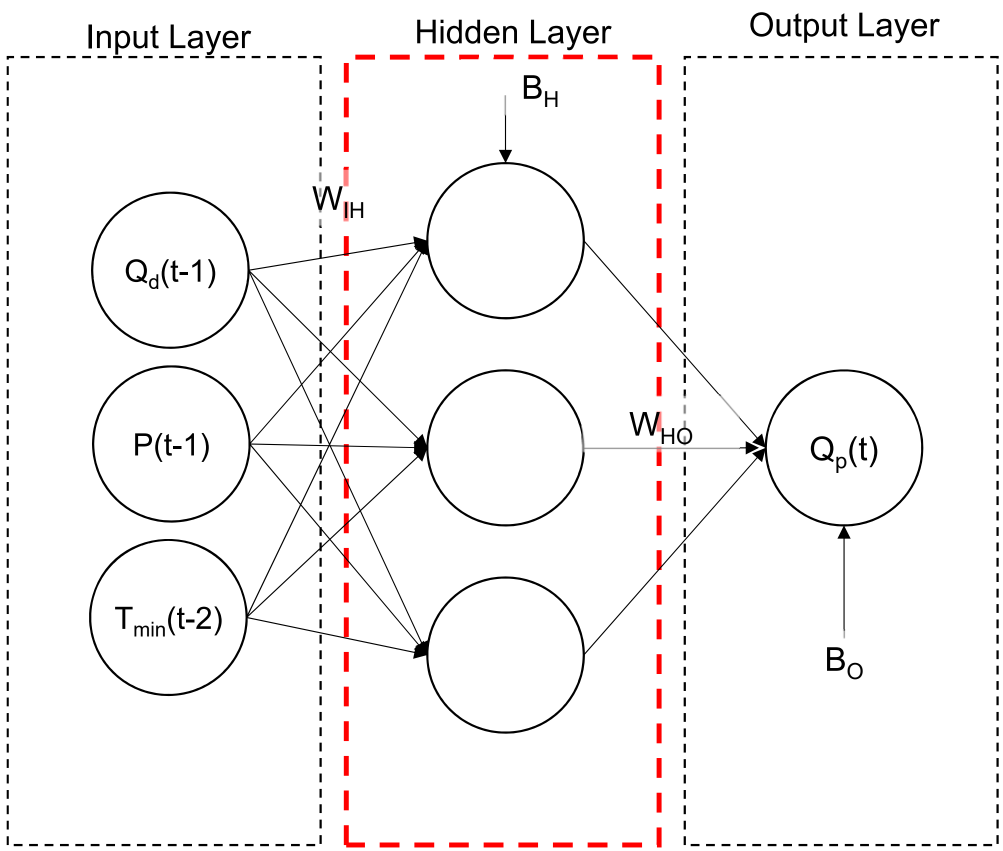
EQR for 18 input parameters



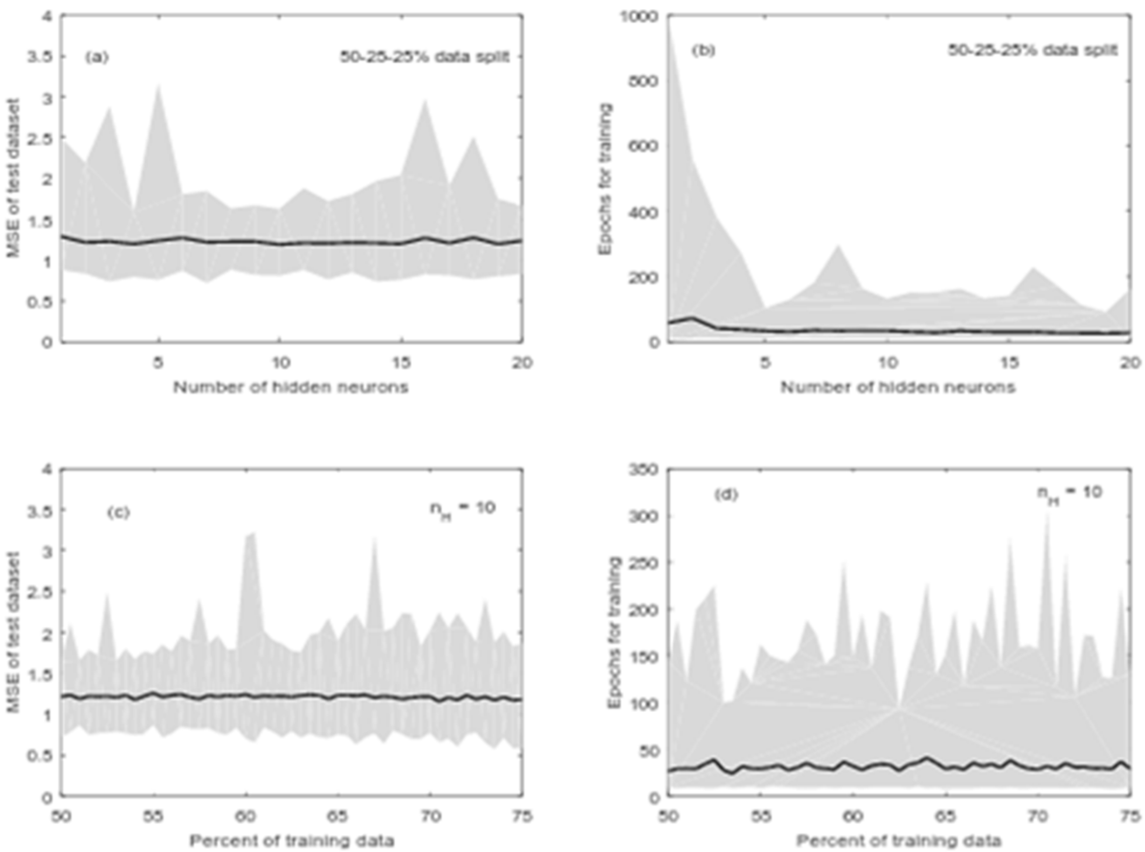
ANN input selection



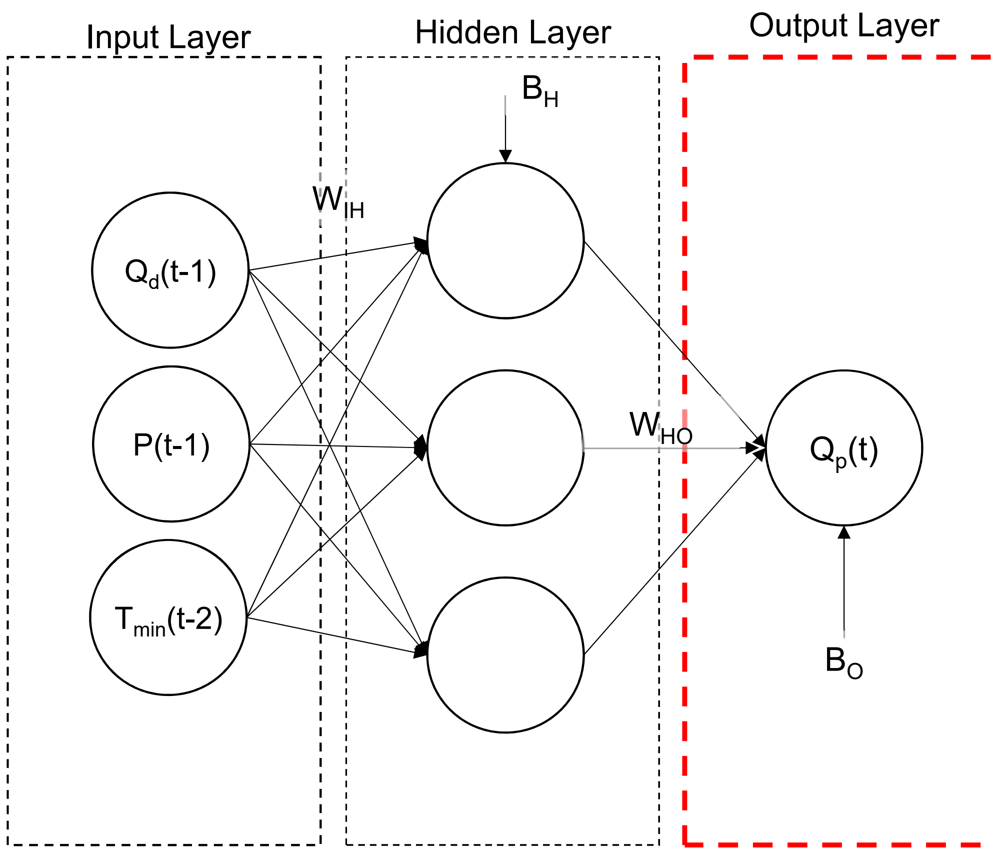
ANN structure selection



ANN architecture selection

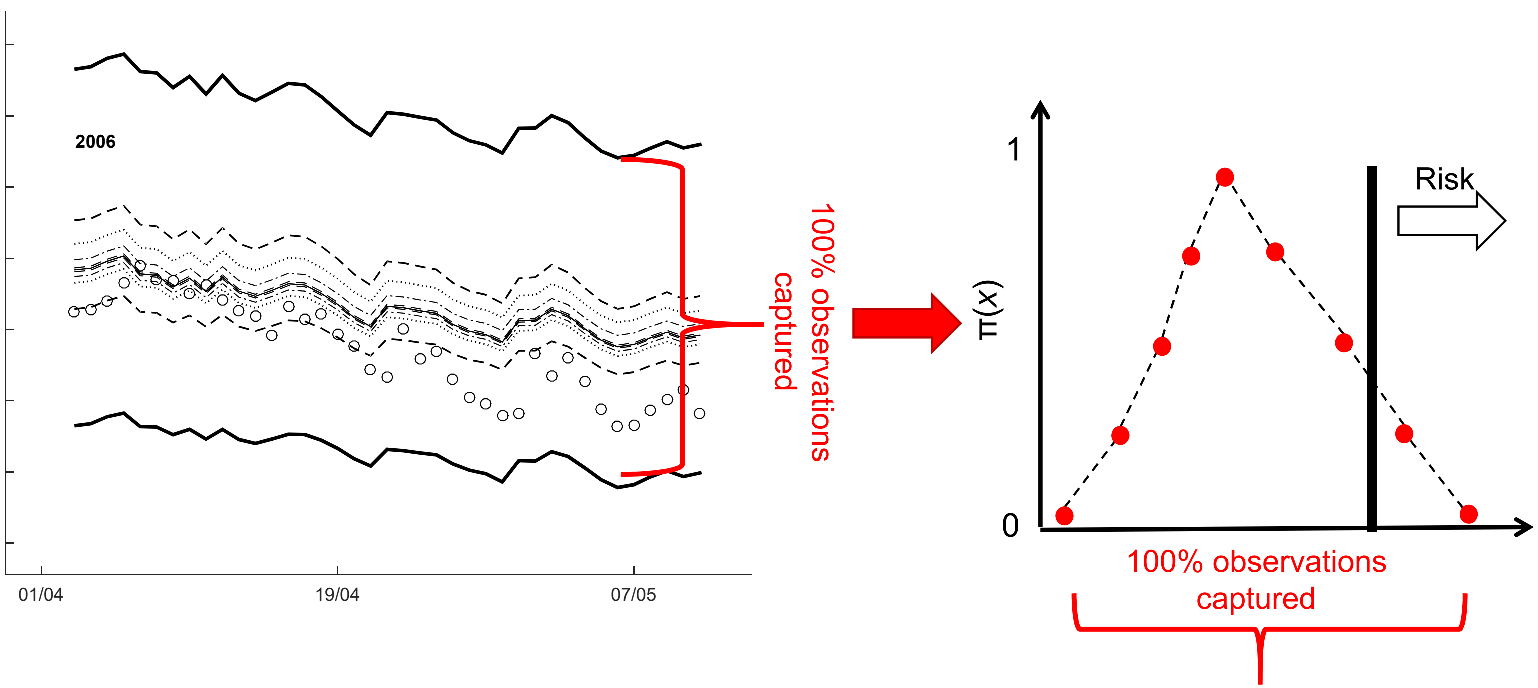


Training a Fuzzy Neural Network

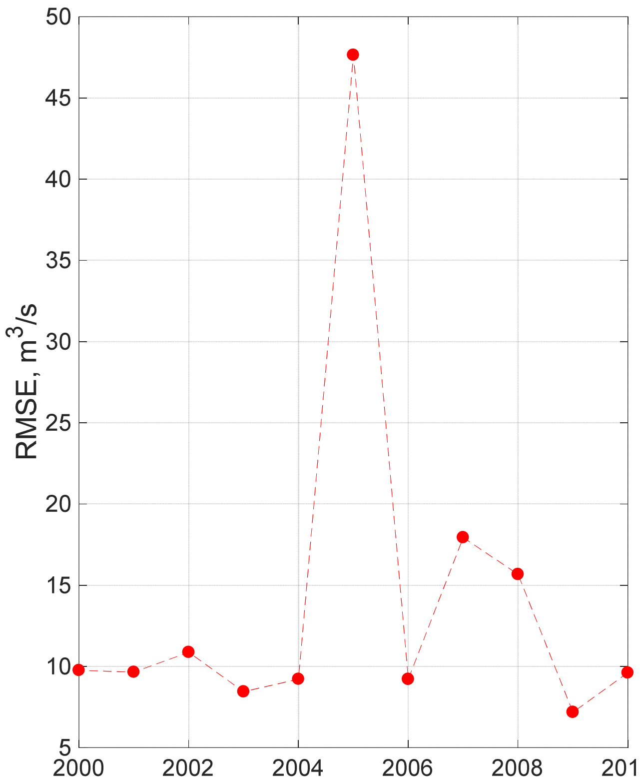


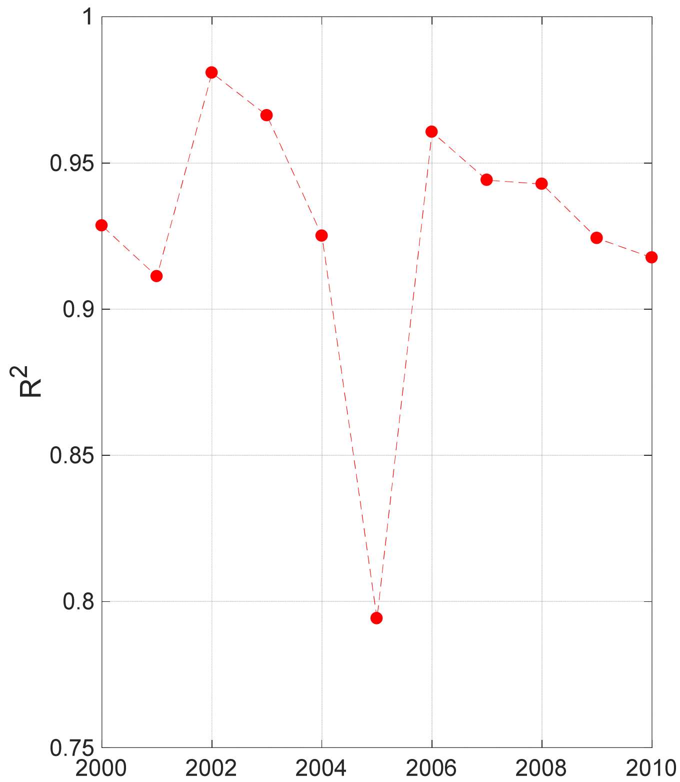
Fuzzy Neural Networks

- Fuzzy number inputs, outputs, weights & biases used for uncertainty quantification
- Upper & lower bounds rather than deterministic output

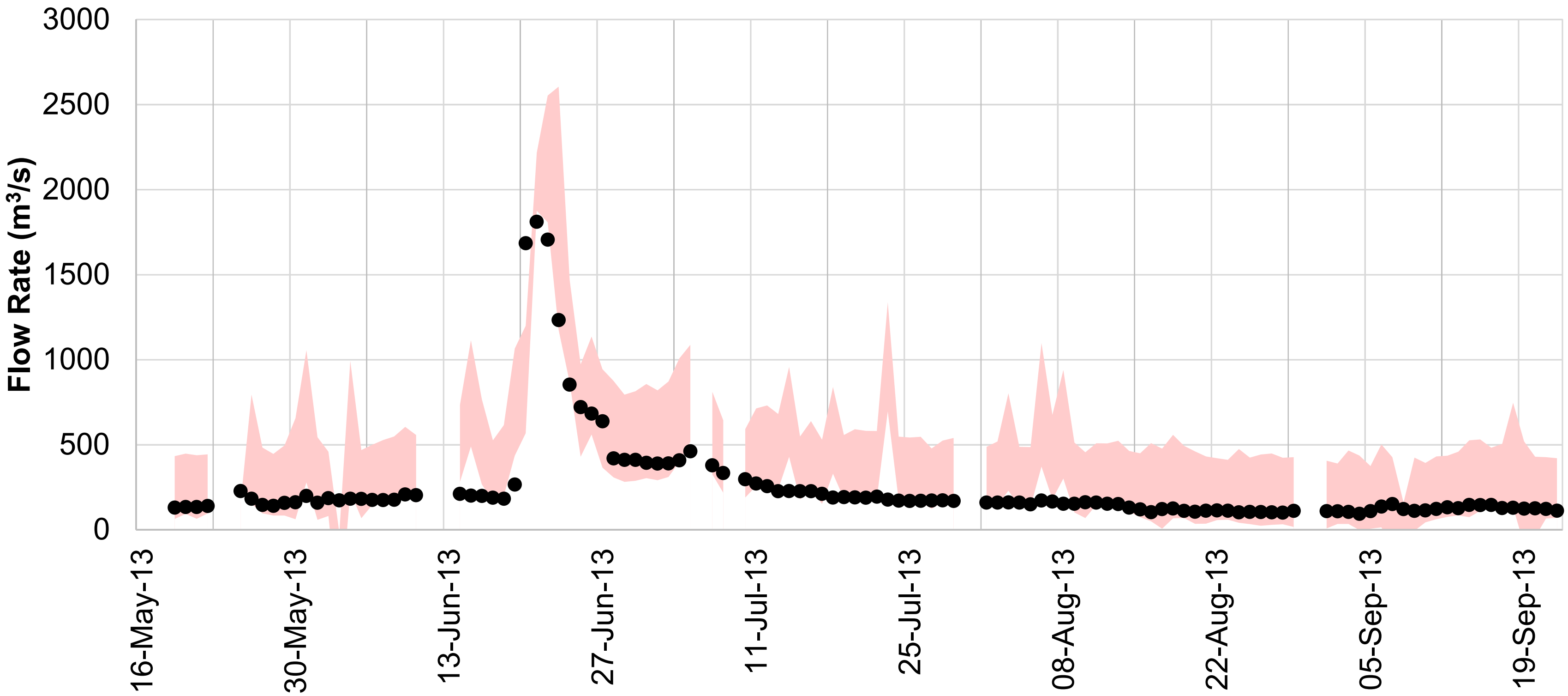


Model performance





Test dataset: 2013 flood results



Conclusions + future work

- CNPSA efficient IVS method
- Search algorithm can replace *ad hoc* approach
- FNN produces intervals for risk analysis
- Real-time updating capability to improve performance
- Include complexity as a criteria for model selection

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References

- Fuzzy Neural Networks:

Khan U.T., & Valeo, C. (2017). Optimising Fuzzy Neural Network Architecture for Dissolved Oxygen Prediction and Risk Analysis. *Water*, 9(6), 381.

Khan, U. T., & Valeo, C. (2016). Dissolved oxygen prediction using a possibility theory based fuzzy neural network. *Hydrology & Earth System Sciences*, 20(6), 2267.

- Data-driven methods for real-time flood prediction

Khan, U. T., & Valeo, C. (2016). Short-Term Peak Flow Rate Prediction and Flood Risk Assessment Using Fuzzy Linear Regression. *Journal of Environmental Informatics*, 28(2), 71-89.

- Combined Neural Pathway Strength Analysis:

Duncan, A. P. (2015). *The Analysis and Application of Artificial Neural Networks for Early Warning Systems in Hydrology and the Environment*. PhD Thesis, University of Exeter, UK.