

ML Applications for Hydraulic

Conventional hydrodynamic numerical models and issues

- Solving water engineering problems typically requires flow characterization, including the prediction of space-time variation of flow depth and flow velocity.
- Physically-based models: NS equations considering external forces with suitable initial-boundary conditions can be used to describe flow characteristics.
 - Applying an accurate numerical method
 - Observed data and expert knowledge are required for
 - Empirical formulae
 - Model calibration and validation.
 - \Rightarrow Computation time consuming
 - \Rightarrow Mostly impossible for large scale modelling

ТШП

ML models

- Trained on dataset can be obtained from
 - Observation,
 - Results of calibrated numerical models.
- \Rightarrow Provide
 - Non-linear relationship between flow parameters
 - Predicted results in the short term.

Water Supply



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Water Supply Vol 21 No 8, 4180 doi: 10.2166/ws.2021.168

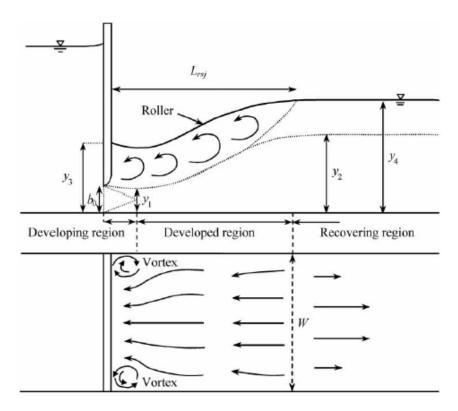
Predicting submerged hydraulic jump characteristics using machine learning methods

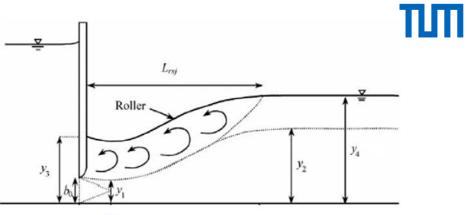
Mohsen Nasrabadi ^(b)^{a,*}, Yaser Mehri^b, Amin Ghassemi^c and Mohammad Hossein Omid^b ^a Department of Water Science and Engineering, Arak University, Karbala Blvd., Basij Sq., Arak 38481-77584, Iran ^b Department of Irrigation & Reclamation Eng., University of Tehran, Daneshkadeh St., Karaj 31587-77871, Iran ^c Queen's University, Kingston, Canada

*Corresponding author. E-mail: nasrabadim@ut.ac.ir, m-nasrabadi@araku.ac.ir

(D) MN, 0000-0001-8061-8836

- Hydraulic jump occurs by converting the supercritical to subcritical flow regimes downstream of hydraulic structures.
 - High energy to erode the channel and river bed.
 - Submerged hydraulic jump downstream of a sluice gate can disperse flow energy.
 - Jump length plays an important role in the economic design of stilling basins and the length of the protection downstream
- Non-linear relationship between the relative energy loss, jump length, Froude number and submergence ratio.





V₁

• Relative submergence depth based on Buckingham theory:

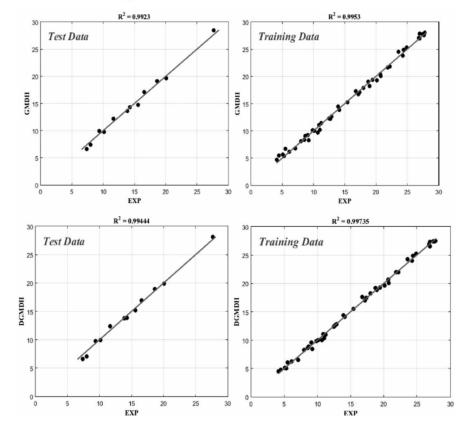
Submerged hydraulic jump

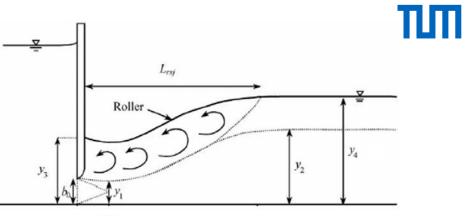
in a smooth bed channel

•

$$\frac{y_3}{y_1} = \mathfrak{I}_1(Fr_1, S)$$
$$S = \frac{y_4 - y_2}{y_2}$$

Researcher/method	MAPE	R ²
Rao & Rajaratnam (1963)	0.1026	0.9921
Abdel-Aal (2004)	0.0540	0.9715
GMDH	0.043	0.9923
DGMDH	0.038	0.9944

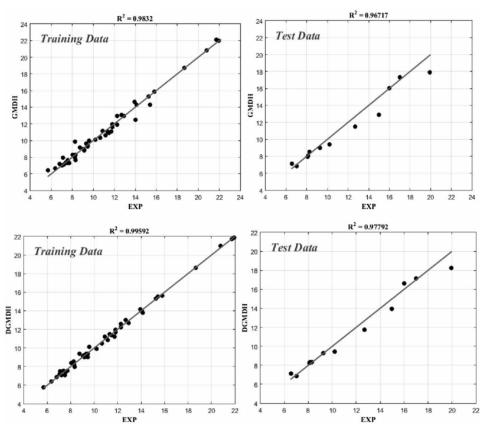


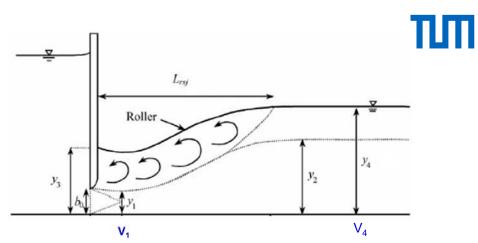


• Submerged jump length:

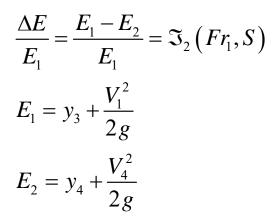
$$\frac{L_{rsj}}{y_2} = \mathfrak{I}_2(Fr_1, S)$$
$$S = \frac{y_4 - y_2}{y_2}$$

Researcher/method	MAPE	R ²
Rao & Rajaratnam (1963)	0.0926	0.9505
Abdel-Aal (2004)	0.0569	0.9478
GMDH	0.0527	0.9671
DGMDH	0.0387	0.9779

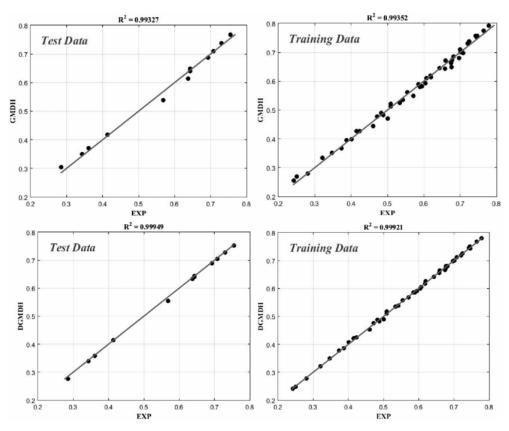




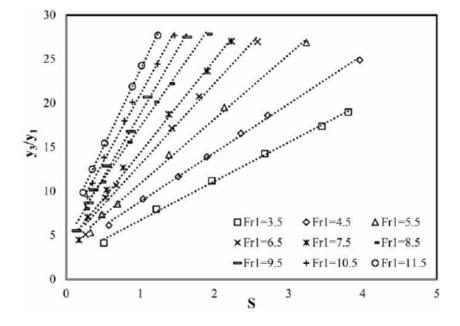
Relative energy loss



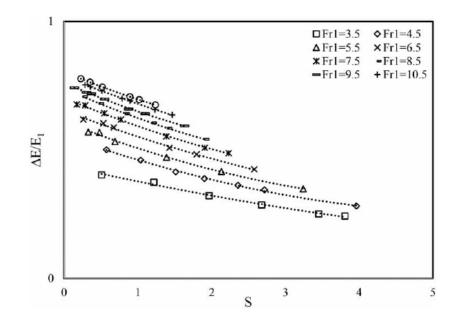
0.1251	0.9980
0.0403	0.9972
0.0192	0.9932
0.0093	0.9994
	0.0403 0.0192



ТШП



Changes in relative submergence depth (y_3/y_1) versus the submergence ratio (S) for different Froude numbers



Changes in the relative energy loss of the submerged hydraulic jump ($\Delta E/E_1$) versus the submergence ratio (S) for different Froude numbers



Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Influence of urban pattern on inundation flow in floodplains of lowland rivers



cience

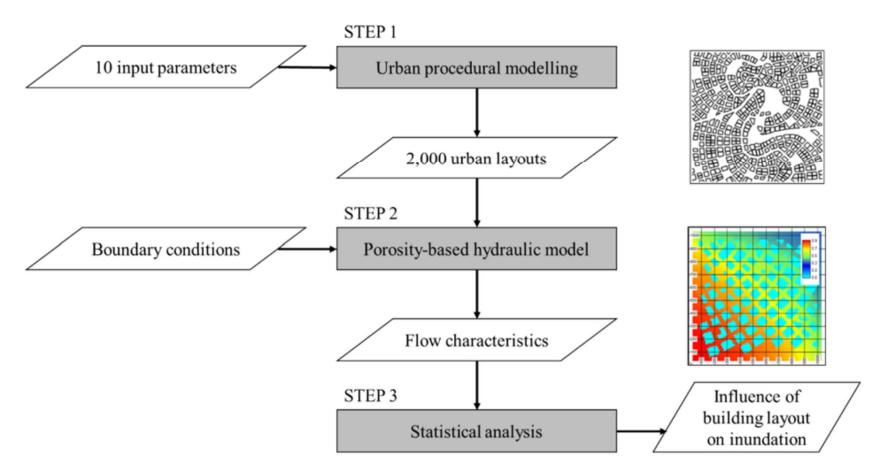
M. Bruwier^{a,*}, A. Mustafa^b, D.G. Aliaga^c, P. Archambeau^a, S. Erpicum^a, G. Nishida^c, X. Zhang^c, M. Pirotton^a, J. Teller^b, B. Dewals^a

^a Hydraulics in Environmental and Civil Engineering (HECE), University of Liege (ULiège), Belgium

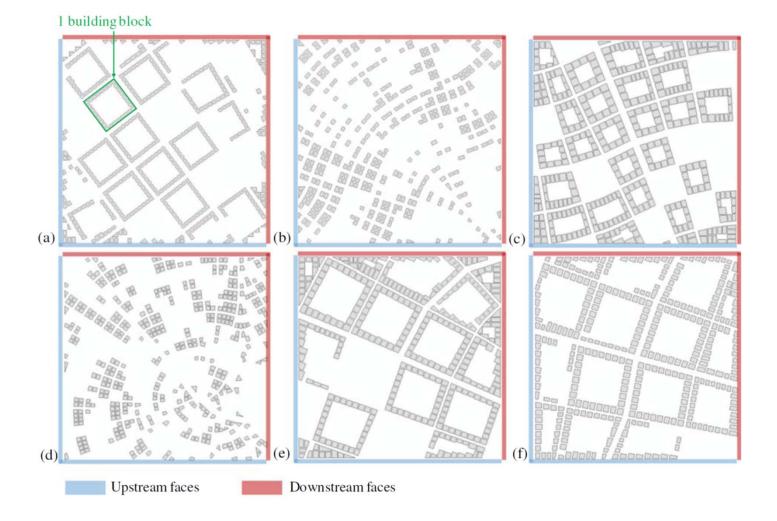
^b Local Environment Management and Analysis (LEMA), University of Liege (ULiège), Belgium

^c Department of Computer Science, Purdue University, USA

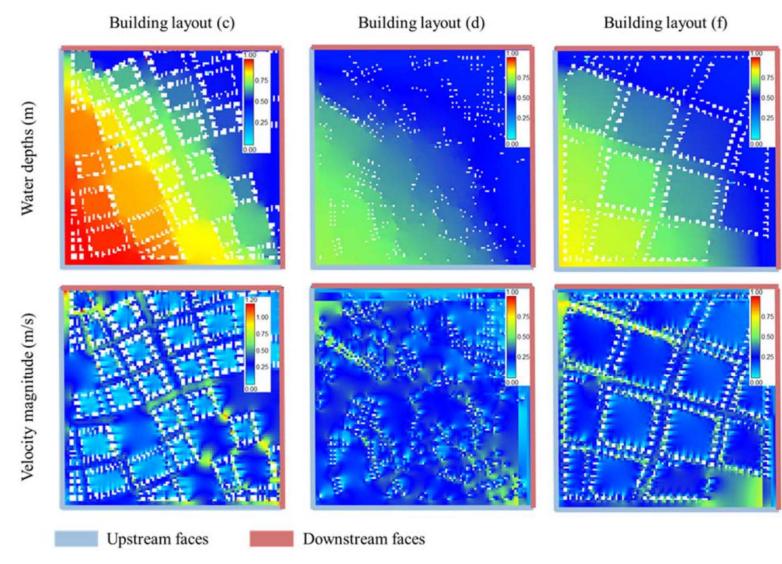
- To investigate the respective influence of various urban pattern characteristics on inundation flow by applying:
 - Steady two-dimensional hydraulic computations for over a set of 2000 synthetic urban patterns (locations and shapes of streets and buildings over a square domain of 1 × 1 km²) with identical hydraulic boundary conditions.
 - Multiple linear regressions for relationships between urban characteristics and the computed inundation water depths.
- This study gives guidelines for more flood-proof urban planning.



Methodology for the determination of the influence of building layout on inundation characteristics

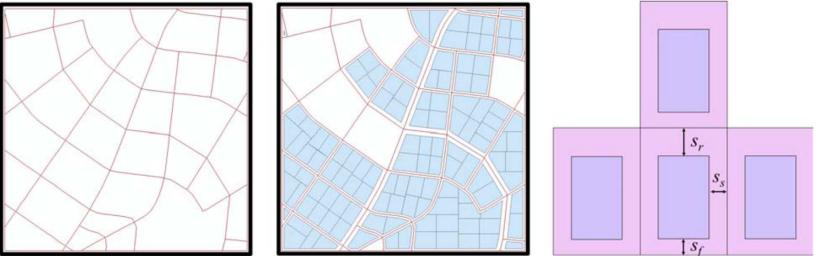


Building footprints for six out of the 2000 layouts used for simulations



Representation of water depths and flow fields for some urban patterns

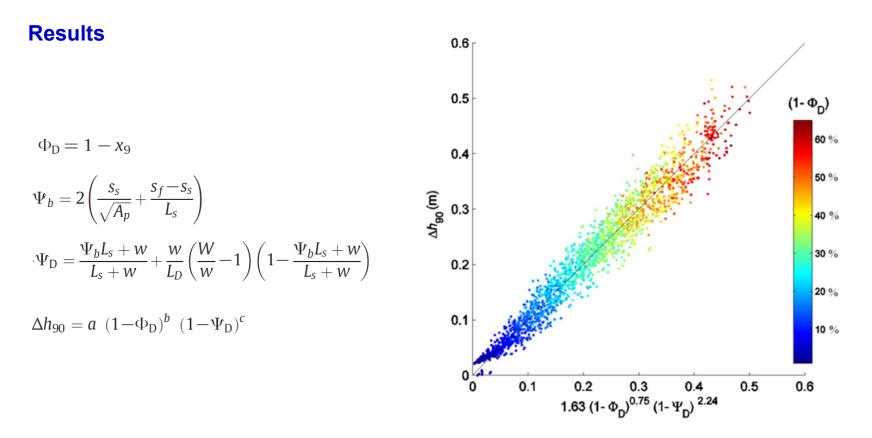




Definition of the tensor field of the streets, the parcels and building footprint in each parcel.

	Urban parameter	Minimum	Maximum	
Ls	Average street length	40 m	400 m	
α	Street orientation	0°	180°	
χ	Street curvature	$0 {\rm km^{-1}}$	10 km^{-1} .	
W	Major street width	16 m	33 m	Urban parameters
W	Minor street width	8 m	16 m	
P_c	Park coverage	5%	40%	
A_p	Mean parcel area	350 m ²	1100 m ²	
Sf	Building front setback	1 m	5 m	
Sr	Building rear setback	1 m	5 m	
Ss	Building side setback	1 m	5 m	





The 90th percentile of the computed water depths along the upstream boundary of the domain is defined based on the district-scale storage Φ_D and conveyance porosities Ψ_D .



Data preprocessing

• 9 urban input parameters

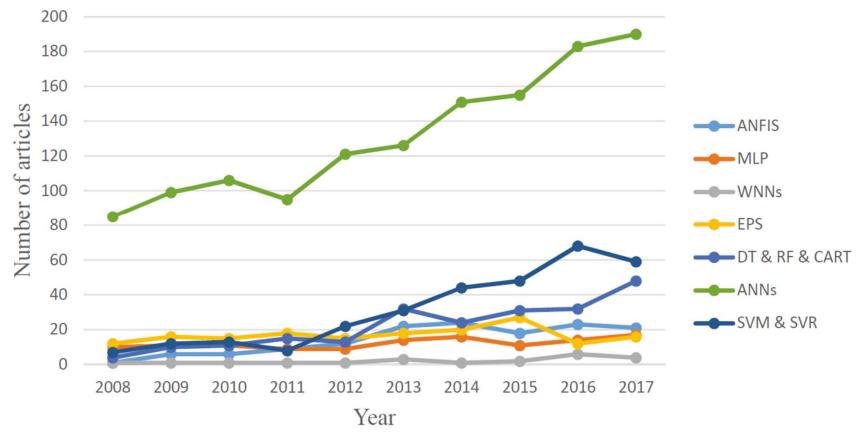
Variable definition	Minimum	Maximum
$x_1 = L_s$	40 m	400 m
$x_2 = \sin(2(\alpha - 45^{\circ})) $	0	1
$x_3 = \chi$	$0 {\rm km^{-1}}$	10 km^{-1}
$x_4 = W + 2 s_f$	18 m	38 m
$x_5 = w + 2 s_f$	10 m	21 m
$x_6 = A_p$	350 m ²	1100 m ²
$x_7 = s_r$	1 m	5 m
$x_8 = s_s$	1 m	5 m
$x_9 = f(L_s, \alpha, \chi, W, w, P_c, A_p, s_r, s_f, s_s)$	0%	43%

• Inundation output: the 90th percentile of the computed water depths along the upstream boundary of the domain (noted Δh_{90}).

MATLAB - Exercise 8.1

- 1. Import Data: Urban_Inundation.xlsx
- 2. Normalize variables
- 3. Divide into 3 datasets: Training (70%); Validation (15%); Testing (15%)
- 4. Design MLP networks with
 - 9 inputs: x₁,.., x₉
 - 1 output: Δh_{90}
- 5. Train and test the networks by applying
 - Case1: one hidden layer and different number of hidden neuron, different activation and training functions
 - Case 2: two hidden layers
- 6. Evaluate network performance and chose the "best" results.





Major ML methods used for flood prediction in the literature. Reference year: 2008 (source: Scopus)

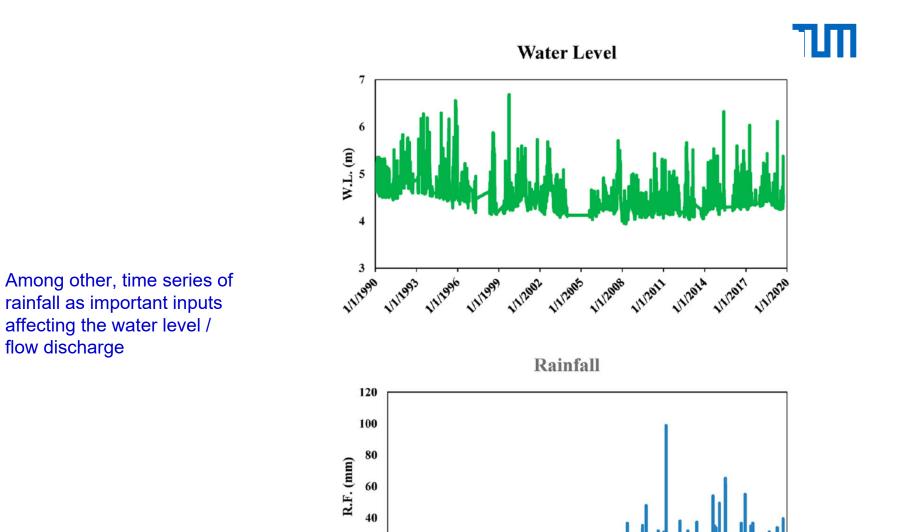


Flood Forecasting Using Machine Learning Methods

Edited by Fi-John Chang, Kuolin Hsu and Li-Chiu Chang Printed Edition of the Special Issue Published in *Water*

www.mdpi.com/journal/water

https://gigamove.rwth-aachen.de/de/download/b7292e4400ba6aecefcc320552c2d0f7



111/2008

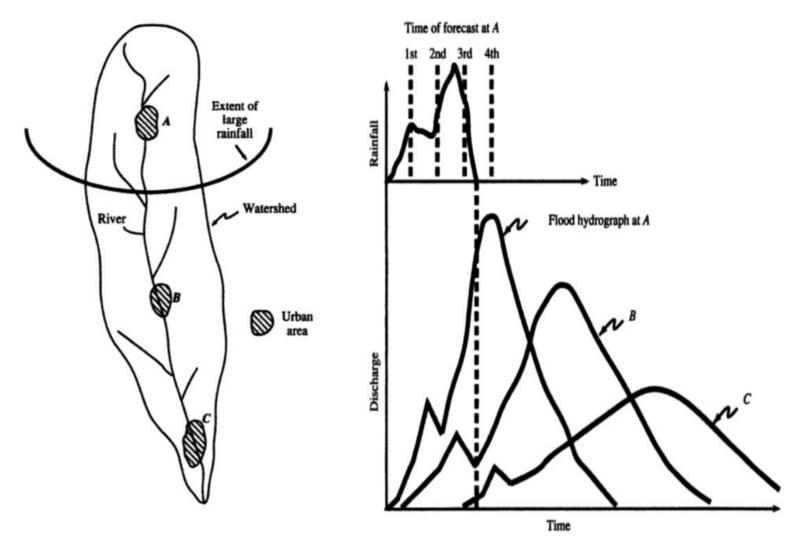
111/2005

111/2002

INPORT

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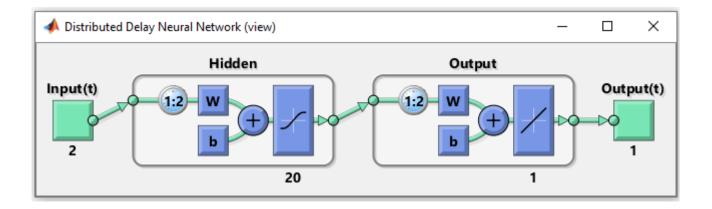




Effect of Lead Time and Flood hydrograph at Downstream Location in a Watershed (L. Mays & Tung, 1992)



Time Series Distributed Delay Networks



nnet = distdelaynet({1:2,1:2},20);
[Xs,Xi,Ai,Ts] = preparets(nnet,Input,Target);



Nonlinear Autoregressive Network with External Input

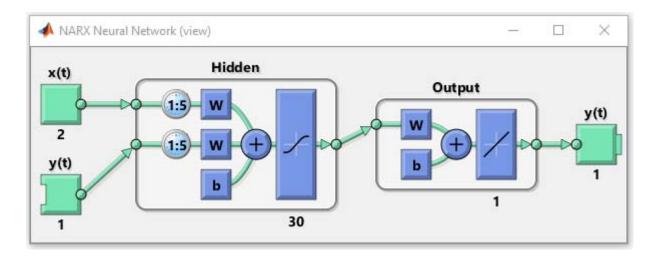
Open

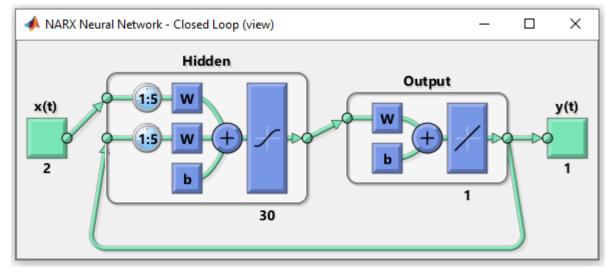
nnet = narxnet(inputDelays, feedbackDelays, hiddenLayerSize, 'open')

Closed

nnet = narxnet(inputDelays, feedbackDelays, hiddenLayerSize, 'closed')

[Xs,Xi,Ai,Ts] = preparets(nnet,Input,{}, Target)





MATLAB - Exercise 8.2

- 1. Import time series data: Flood_Data.xlsx
- 2. Impute the missing data
- 3. Normalize variables
- 4. Design, train and test two following networks
 - I. TS-ANN (Time Series Distributed Delay Networks) with 4 inputs (flow discharge and precipitation at two former time steps) and one output (flow discharge) at the present time.
 - II. Nonlinear Autoregressive Network with External Input
- 5. View the networks and evaluate the results.



Data for your project

1. Germany

https://www.gkd.bayern.de/de/fluesse/abfluss/isar/grafrath-16603000/download?zr=gesamt&beginn=01.07.2019&ende= 23.07.2019&wertart=ezw

2. USA https://www.sciencebase.gov/catalog/items?q=&filter=tags%3 Dsuspended+material+%28water%29

https://waterdata.usgs.gov/co/nwis/uv/?site_no=06708690&P ARAmeter_cd=00045,72192