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Cavitation modelling and Machine Learning integration in the Digital Twin prediction of extreme pressure heads

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Content

Summary of the content

- This research presents a methodology that integrates both experimental and modelling strategies, as well as Machine Learning (ML), to analyse hydraulic transients and cavitation occurrence.
- Laboratory tests were conducted to replicate water hammer events and validate numerical simulations using an adapted mathematical cavitation model (CM) and Hammer, a commercial one, from Bentley. These models, based on the 1D Method of Characteristics (MOC), incorporate discrete cavities in pipe sections when the vapour pressure is reached. Comparing experimental results with CM outputs offers valuable insights into the Digital Twin (DT) simulation tools.
- The study also includes a ML framework for predicting key hydraulic responses, such as maximum (*Hmax*) and minimum (*Hmin*) pressure heads, based on water flow rates and pipe diameters. Using a dataset spanning flow rates from 25 to 950 l/h and diameters from 0.005 to 0.06 m, the ML model was trained and validated through 5-fold cross-validation. A three-layered neural network emerged as the most effective model, achieving high accuracy: R^2 0.97 (*Hmax*) and 0.98 (*Hmin*) during testing.
- The model could accurately forecast *extreme pressures, with Hmin* being especially valuable for identifying cavitation risks, enabling proactive system management and design optimisation without the need for complex hydraulic simulations.

1. Introduction

Ramos et al. (2022) - synthesised experimental and numerical insights into two-phase flow dynamics, including pressure surges, cavitation, and ventilation. Their study examined the interplay between air valve behaviour and transient flow interactions, providing a comprehensive view of how ventilation and cavitation phenomena influence pipeline performance under dynamic conditions [7].

H.M. Ramos, V.S. Fuertes-Miquel, E. Tasca,O.E. Coronado-Hernández, M. Besharat, L. Zhou, B. Karney, "Concerning Dynamic Effects in Pipe Systems with Two-Phase Flows: Pressure Surges, Cavitation, and Ventilation". Water 2022, 14, 2376. https://doi.org/10.3390/w14152376 .

The operational effectiveness of venting contributes significantly to:

- System Protection: By eliminating air pockets, they reduce the risk of pressure surges and water hammer events.
- Energy Efficiency: Maintaining air-free flow minimises head loss and improves pump performance.
- Preventive Maintenance: Regular air expulsion prevents corrosion in pipe crowns and maintains measurement accuracy in flow meters.

Proper selection and installation require careful consideration of system pressure ratings, flow conditions, and the specific air handling capacity needed for optimal performance in different pipeline configurations.

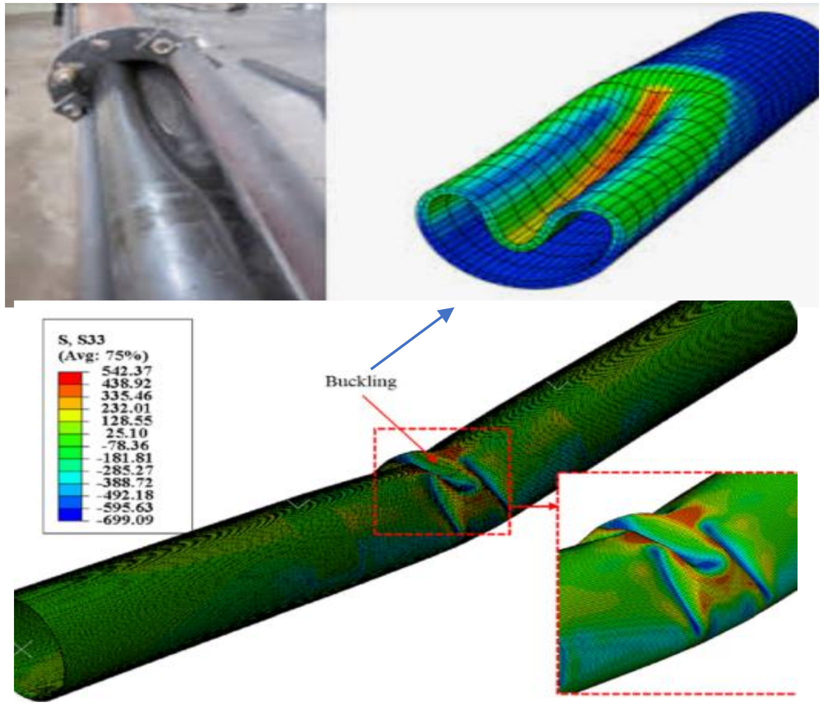
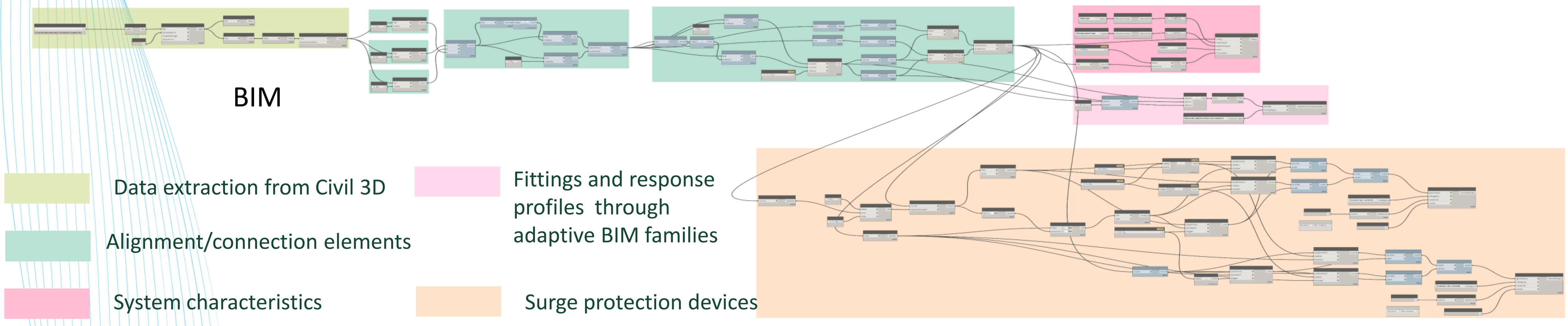


Figure 1 - Buckling collapse of a pipe

Active protection devices with real-time monitoring networks, with pressure transducers and flow meters, BIM and Digital Twin (DT) with automated response algorithms that trigger protective devices are crucial, as well as predictive control systems using ML to anticipate transient events.

The emerging security technologies use recent advancements enhancing hydraulic system security with smart surge mitigation, Internet of Things (IoT)-enabled valves with adaptive response profiles, distributed acoustic sensing for early transient detection, blockchain-based maintenance logs for surge protection devices, advanced materials with self-healing pipe coatings that repair small cracks, nanocomposite materials with improved fatigue resistance and hybrid protection systems with combined mechanical and electronic surge arrestors, hydraulic dampers with tuneable characteristics and artificial intelligence optimized protection device networks.



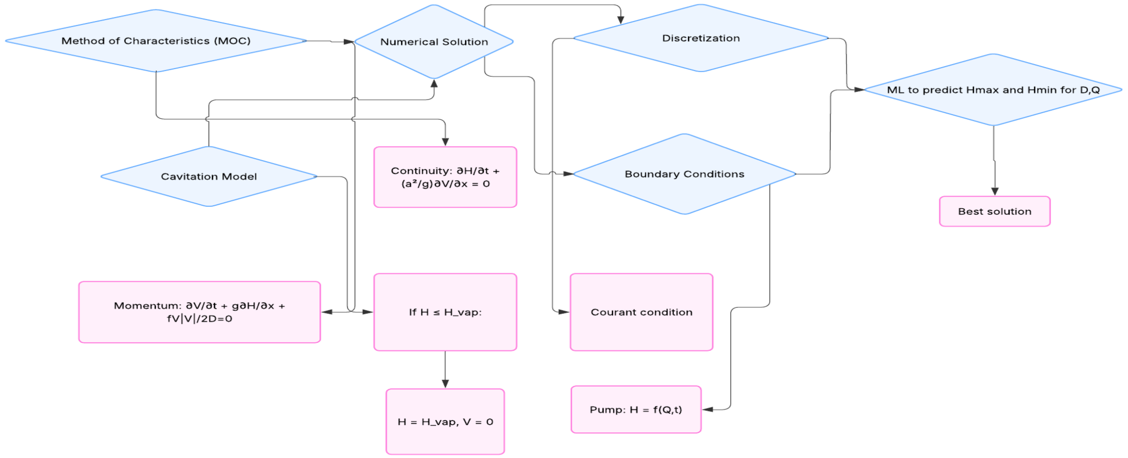
2. METHODOLOGY

The methodology for analysing hydraulic transients with cavitation and Machine Learning (ML) combines classical hydraulic modelling through the Method of Characteristics (MOC) with modern predictive approaches. The process starts with the Method of Characteristics (MOC), which is a well-established numerical tool for solving transient flow problems in pressurised systems. It provides a numerical solution by solving the governing equations of unsteady flow.
The system requires the discretisation of the pipeline and the definition of boundary conditions (such as reservoirs, pump characteristics and outlet conditions). Within the solution framework, a cavitation model is incorporated.

Finally, the methodology integrates Machine Learning (ML), where the ML model predicts maximum and minimum heads (*Hmax* and *Hmin*) for given flow and pipe diameter conditions (*D, Q*). This allows for getting the best solution with a rapid estimation of extreme transient responses without requiring a full simulation each time.

Numerical modelling

This methodology merges a physics-based transient flow solver (MOC with cavitation modelling) and a data-driven predictive layer (ML). This hybrid framework leverages the accuracy of numerical models with the speed of ML to efficiently evaluate transient pressures and identify optimal solutions.



Discrete vapour cavities can open at all pipe sections. Hence, macro cavitation can be characterised by the existence of a vapour cavity volume $\forall_{i,j}$ at the pipe section i and for the time j as follows:

$$\forall_{i,j} = \forall_{i,j-1} + \frac{(Q_{Ri,j} + Q_{Ri,j-1} - Q_{Li,j} - Q_{Li,j-1})\Delta t}{2}$$

This condition is imposed when the absolute pressure drops to the liquid vapour pressure (vaporous cavitation inception) H_{IC} (ca. -8 to -10 m depending on the site conditions), and maintains this value if the cavity volume is positive.

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(General)                                   calculo

' Reservatorio de Montante

H2(1) = HM
QD2(1) = QE1(2) + (H2(1) - H1(2) - R * Abs(QE1(2)) * QE1(2)) / A
QE2(1) = QD2(1)

' Pontos Interiores

For i = 2 To n

H2(i) = TV + Z(i)
QE2(i) = QD1(i - 1) - (H2(i) - H1(i - 1) + R * Abs(QD1(i - 1)) * QD1(i - 1)) / A
QD2(i) = QE1(i + 1) + (H2(i) - H1(i + 1) - R * Abs(QE1(i + 1)) * QE1(i + 1)) / A
'V(i) = V(i) + (QD2(i) + QD1(i) - QE2(i) - QE1(i)) * DT / 2
V(i) = V(i) + (QD2(i) + QD2(i) - QE2(i) - QE2(i)) * DT / 2

If V(i) < 0 Then
V(i) = 0
H2(i) = (H1(i - 1) + H1(i + 1) + A * (QD1(i - 1) - QE1(i + 1)) - R * (Abs(QD1(i - 1)) * QD1(i - 1) - Abs(QE1(i + 1)) * QE1(i + 1))) / 2
QE2(i) = (QD1(i - 1) + QE1(i + 1) + (H1(i - 1) - H1(i + 1) - R * (Abs(QD1(i - 1)) * QD1(i - 1) + Abs(QE1(i + 1)) * QE1(i + 1))) / A) / 2
QD2(i) = QE2(i)
End If

Next i

' Reservatorio de Jusante com Valvula
If TF = 0 Then
QD2(n1) = 0
Else
If T > TF Then
QD2(n1) = 0
Else
QD2(n1) = Q * (1 - T / TF)
End If
End If
H2(n1) = TV + Z(n1)
QE2(n1) = QD1(n) - (H2(n1) - H1(n) + R * Abs(QD1(n)) * QD1(n)) / A
'V(n1) = V(n1) + (QD2(n1) + QD1(n1) - QE2(n1) - QE1(n1)) * DT / 2
V(n1) = V(n1) + (QD2(n1) + QD2(n1) - QE2(n1) - QE2(n1)) * DT / 2
```

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A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
Start				S. Jusante				S. Media					X	Z	Hmax	Hmin
Q (l/h)=	675		T	Q	QV	H	V	QE	QD	H	V					
L (m)=	85		0.00	0.0002	0.0002	30.0	0.0000	0.0002	0.0002	28.8	0.0000		0	0	30	30
D (m)=	0.02		0.00	0.0002	0.0002	32.7	0.0000	0.0002	0.0002	28.8	0.0000		4.3	0.04	73.56	-7.597
C (m/s)=	1150		0.01	0.0002	0.0002	37.9	0.0000	0.0002	0.0002	28.8	0.0000		8.50	0.081	73.6	-7.696
HM (m)=	30		0.01	0.0001	0.0001	43.1	0.0000	0.0002	0.0002	28.8	0.0000		12.75	0.121	73.64	-7.728
N=	20		0.01	0.0001	0.0001	48.3	0.0000	0.0002	0.0002	28.8	0.0000		17	0.162	73.6	-8.038
TF (s)	0.05		0.02	0.0001	0.0001	53.5	0.0000	0.0002	0.0002	28.8	0.0000		21.25	0.202	81.21	-7.998
TV (m)=	-8.2		0.02	0.0001	0.0001	58.7	0.0000	0.0002	0.0002	28.8	0.0000		25.5	0.243	91.19	-7.957
			0.03	0.0001	0.0001	63.9	0.0000	0.0002	0.0002	28.8	0.0000		29.75	0.283	98.9	-7.917
			0.03	0.0001	0.0001	69.1	0.0000	0.0002	0.0002	28.8	0.0000		34	0.324	98.96	-7.876
			0.03	0.0001	0.0001	74.4	0.0000	0.0002	0.0002	28.8	0.0000		38.25	0.364	99.02	-7.836
HJ (m)=	27.554868		0.04	0.0000	0.0000	79.6	0.0000	0.0002	0.0002	28.8	0.0000		42.5	0.405	101.1	-7.795
TT (s)=	5		0.04	0.0000	0.0000	84.8	0.0000	0.0002	0.0002	33.9	0.0000		46.75	0.445	109.5	-7.748
U (m/s)=	0.596831		0.04	0.0000	0.0000	90.1	0.0000	0.0002	0.0002	39.0	0.0000		51	0.486	109.6	-7.714
f	0.0316568		0.05	0.0000	0.0000	95.3	0.0000	0.0001	0.0001	44.1	0.0000		55.25	0.559	109.7	-7.641
dH (m)	2.4451323		0.05	0.0000	0.0000	98.1	0.0000	0.0001	0.0001	49.2	0.0000		59.5	0.651	109.7	-7.549
dH/Q2	5.37E-06		0.06	0.0000	0.0000	98.2	0.0000	0.0001	0.0001	54.4	0.0000		63.75	0.742	109.6	-7.458
			0.06	0.0000	0.0000	98.2	0.0000	0.0001	0.0001	59.5	0.0000		68	0.834	109.9	-7.366
HJ (m)=	27.554868		0.06	0.0000	0.0000	98.3	0.0000	0.0001	0.0001	64.7	0.0000		72.25	0.925	109.9	-7.275
			0.07	0.0000	0.0000	98.3	0.0000	0.0001	0.0001	69.9	0.0000		76.5	1.017	109.9	-7.183
			0.07	0.0000	0.0000	98.4	0.0000	0.0001	0.0001	75.1	0.0000		80.75	1.108	109.8	-7.092
			0.07	0.0000	0.0000	98.5	0.0000	0.0001	0.0001	80.3	0.0000		85	1.2	110	-7
Re=	9111.9242		0.08	0.0000	0.0000	98.5	0.0000	0.0000	0.0000	85.5	0.0000					
k (mm)=	0		0.08	0.0000	0.0000	98.6	0.0000	0.0000	0.0000	90.7	0.0000					
	0.01		0.09	0.0000	0.0000	98.7	0.0000	0.0000	0.0000	95.9	0.0000					
	0.0381489		0.09	0.0000	0.0000	98.7	0.0000	0.0000	0.0000	98.7	0.0000					
	0.0307641		0.09	0.0000	0.0000	98.8	0.0000	0.0000	0.0000	98.8	0.0000					
	0.0317978		0.10	0.0000	0.0000	98.8	0.0000	0.0000	0.0000	98.8	0.0000					
	0.0316356		0.10	0.0000	0.0000	98.9	0.0000	0.0000	0.0000	98.9	0.0000					
	0.0316606		0.10	0.0000	0.0000	99.0	0.0000	0.0000	0.0000	99.0	0.0000					
	0.0316568		0.11	0.0000	0.0000	99.0	0.0000	0.0000	0.0000	99.0	0.0000					
			0.11	0.0000	0.0000	99.1	0.0000	0.0000	0.0000	99.1	0.0000					
X (m)	Z (m)		0.11	0.0000	0.0000	99.1	0.0000	0.0000	0.0000	94.2	0.0000					
			0.12	0.0000	0.0000	99.2	0.0000	0.0000	0.0000	89.2	0.0000					
0.00	0		0.12	0.0000	0.0000	99.3	0.0000	0.0000	0.0000	84.3	0.0000					
52.50	0.5		0.13	0.0000	0.0000	99.3	0.0000	-0.0001	-0.0001	79.3	0.0000					
85.00	1.2		0.13	0.0000	0.0000	99.4	0.0000	-0.0001	-0.0001	74.3	0.0000					
			0.13	0.0000	0.0000	99.4	0.0000	-0.0001	-0.0001	69.3	0.0000					
			0.14	0.0000	0.0000	99.5	0.0000	-0.0001	-0.0001	64.2	0.0000					
			0.14	0.0000	0.0000	99.6	0.0000	-0.0001	-0.0001	59.2	0.0000					
			0.14	0.0000	0.0000	99.6	0.0000	-0.0001	-0.0001	54.1	0.0000					
			0.15	0.0000	0.0000	99.7	0.0000	-0.0001	-0.0001	49.1	0.0000					
			0.15	0.0000	0.0000	89.8	0.0000	-0.0001	-0.0001	44.0	0.0000					

R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN
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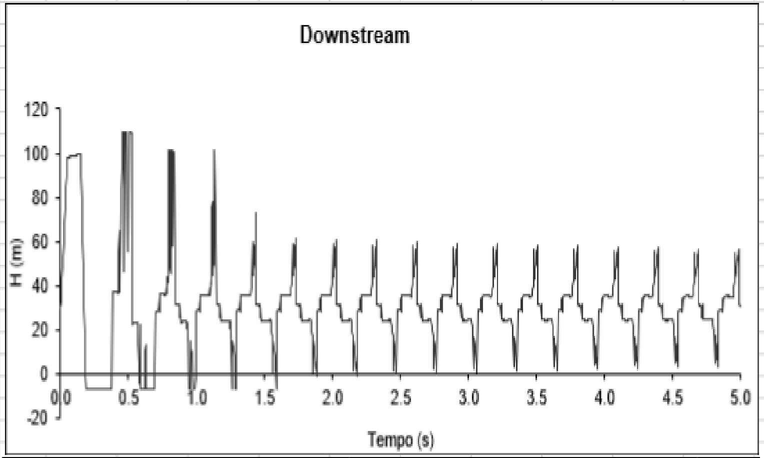
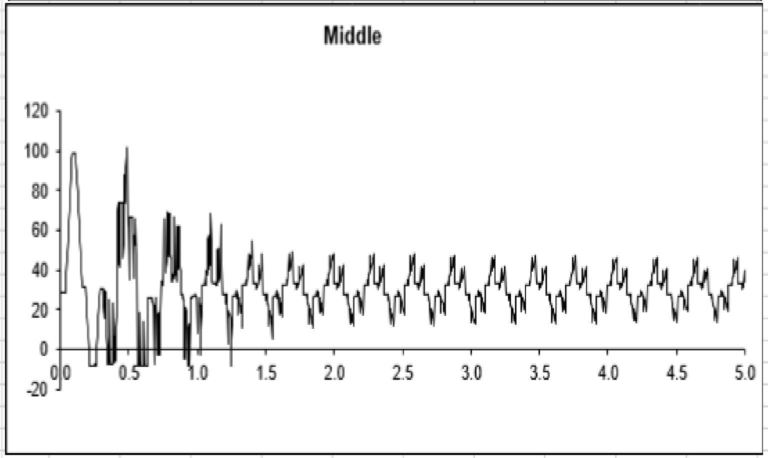
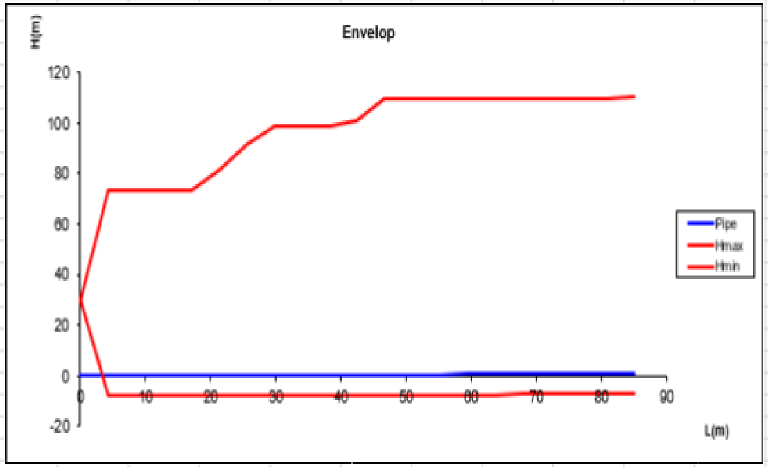
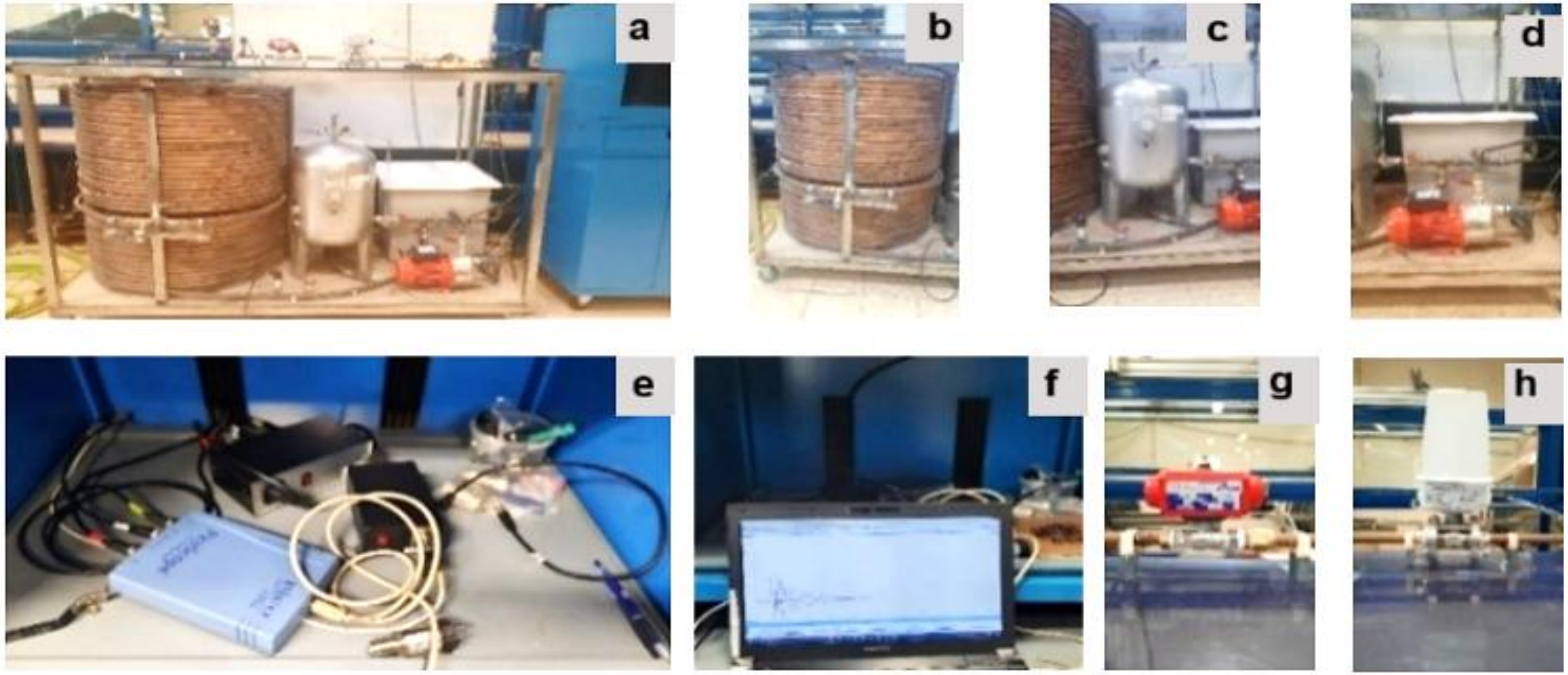




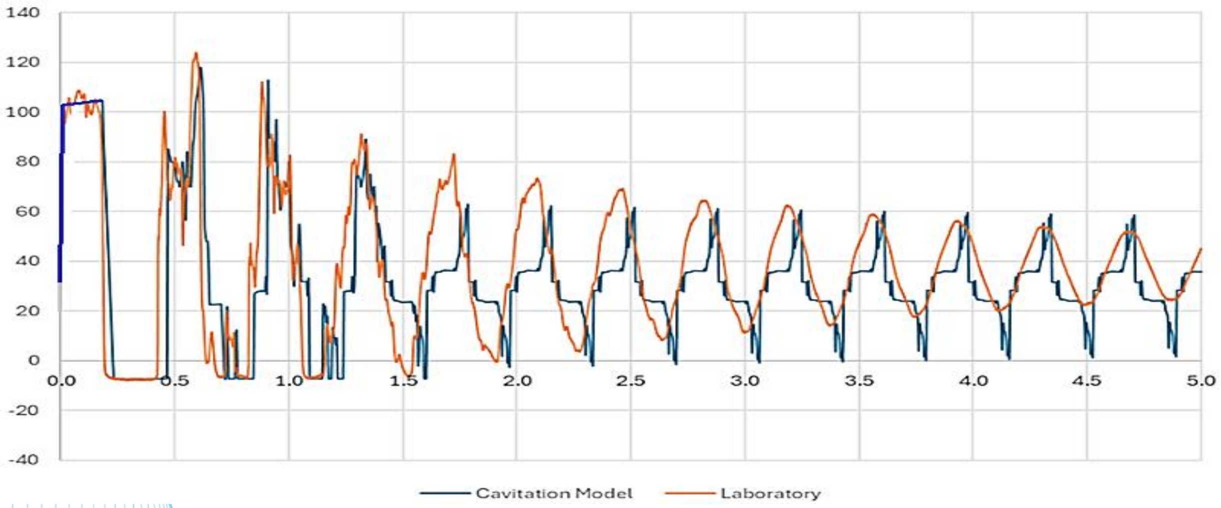


Experimental Setup

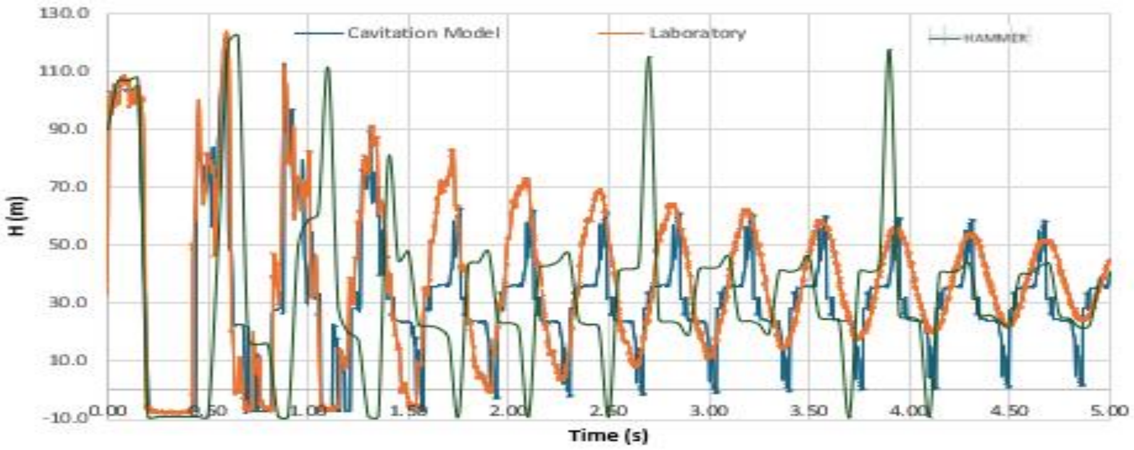
It consists of a coiled copper pipe of approximately 100 m in length, with an inside diameter of 20 mm and a wall thickness of 1 mm. A storage tank of 125 l capacity, to feed a pump, with a nominal flow rate of 4.5 m³/h and a head of 43 m. Downstream of the pump, there is a hydropneumatic of 60 l, in stainless steel and a nominal pressure of 6 bar. At the end, there are two valves, a globe valve with a nominal diameter 15 (DN15 ½) and a ball valve with a DN ¾ .



3. RESULTS AND DISCUSSION



Experiments and calibration of the CM based on experiments.



Comparison between models and lab tests

ML algorithms application

The use of water flow rate (Q) and internal pipe diameter (D) as input features reflects a physically grounded approach to modelling hydraulic transients. These variables directly influence wave propagation speed, pressure head amplitude, and cavitation susceptibility, such as:

- Flow Rate (Q): Higher flow rates increase kinetic energy, potentially amplifying pressure surges and transient oscillations.
- Pipe Diameter (D): Smaller diameters intensify velocity gradients and frictional losses, which can exacerbate pressure drops and cavitation onset.

ML algorithms are trained to predict key hydraulic responses - specifically, the maximum (*Hmax*) and minimum (*Hmin*) pressure heads - based on the selected input variables such as water flow rate (Q) and internal pipe diameter (D). The simulation setup includes a wide range of flow rates from 25 to 950 l/h and pipe diameters from 0.005 to 0.06 m in a total of 32 series of case studies.

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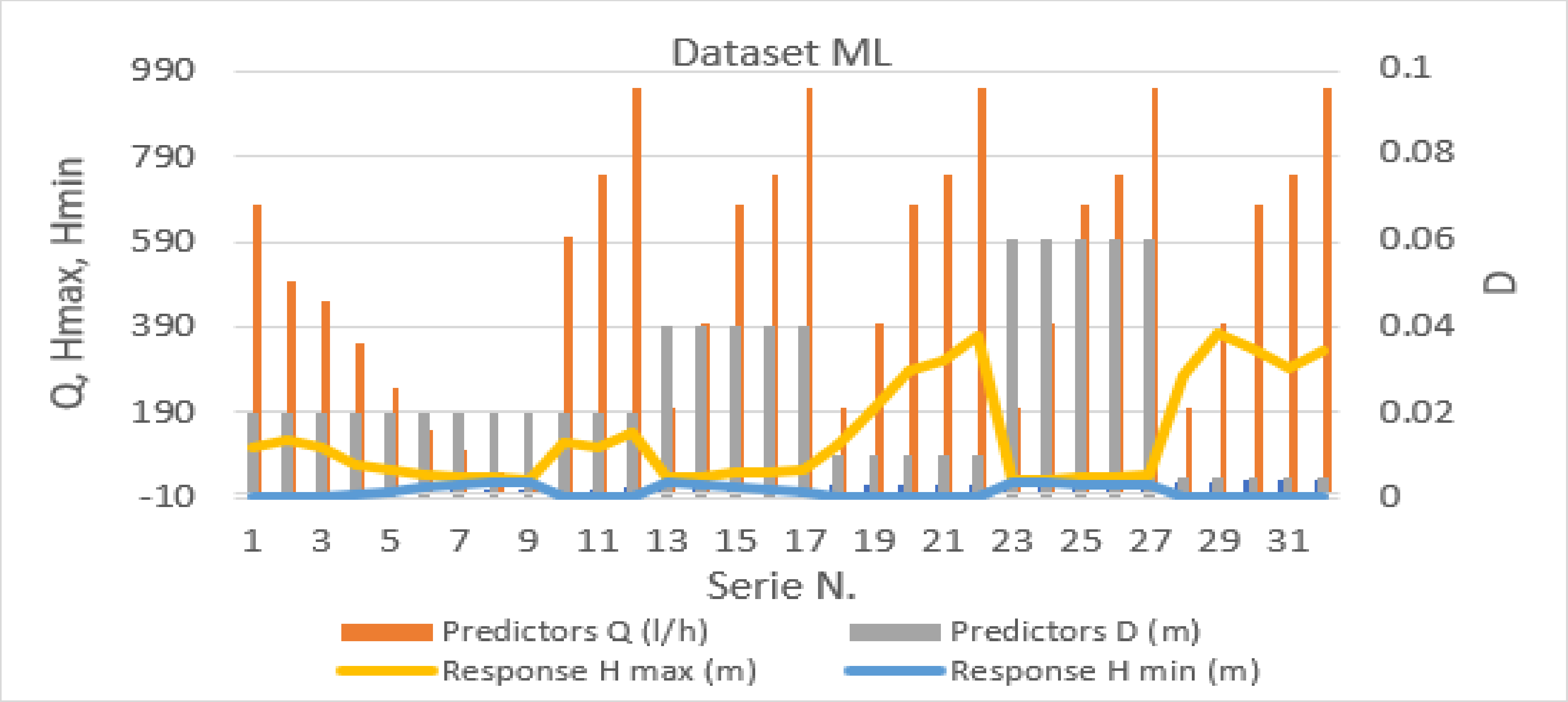
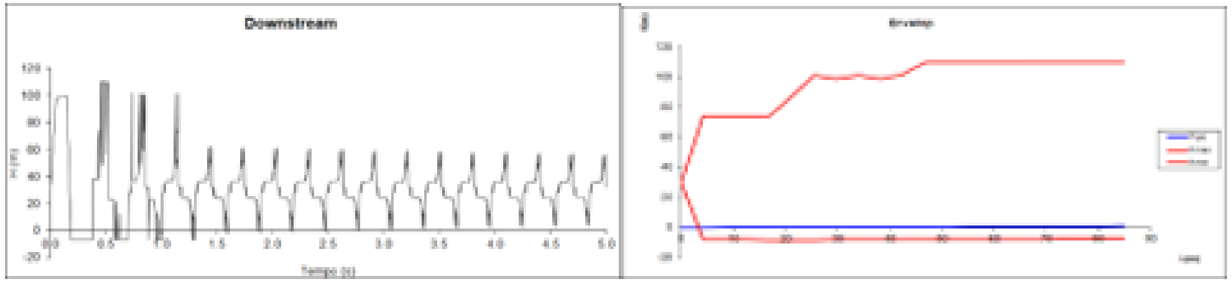
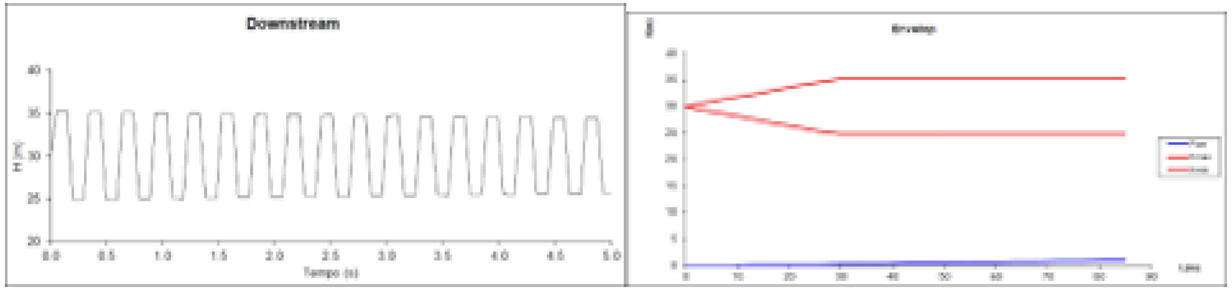


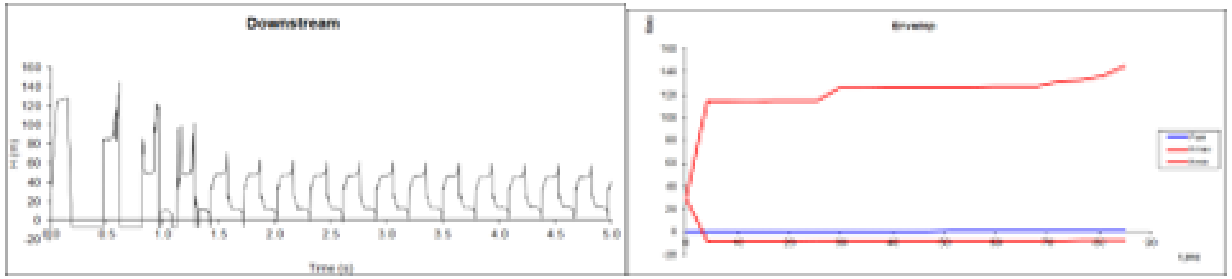
Case 1 – high Q medium D



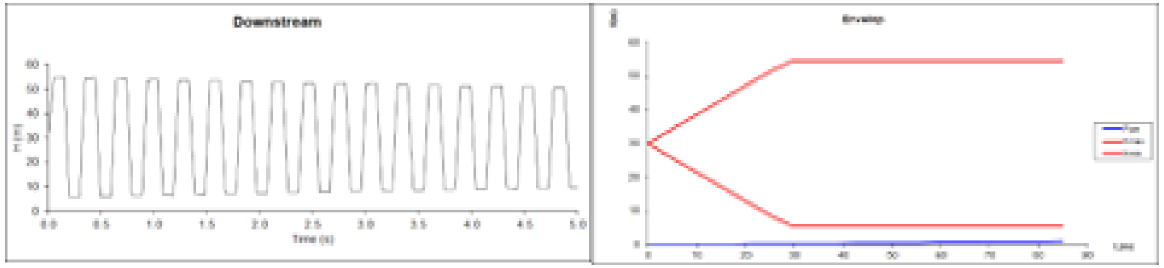
Case 8- small Q and medium D



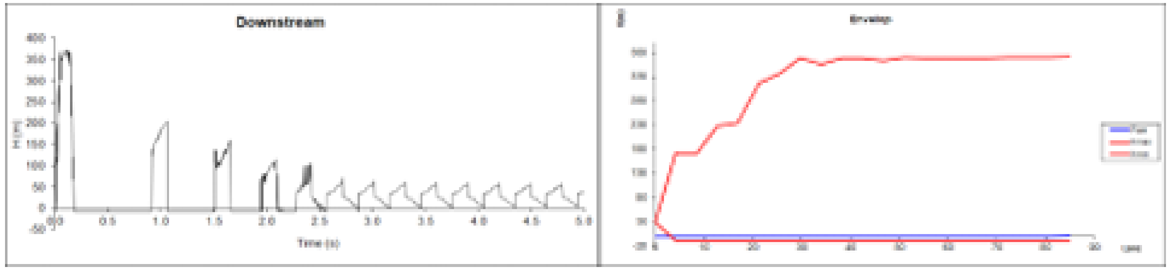
Case 12 – medium D and very high Q



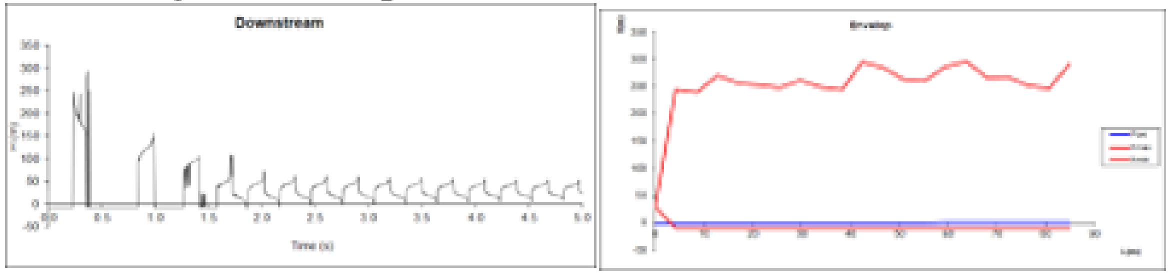
Case 17 – higher D and very high Q



Case 22 - small D and very high Q

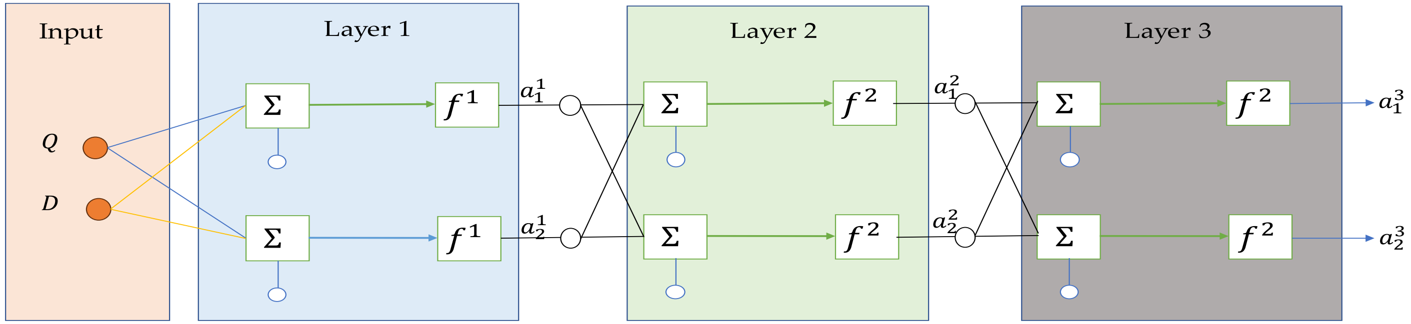


Case 31 – very small D and high Q



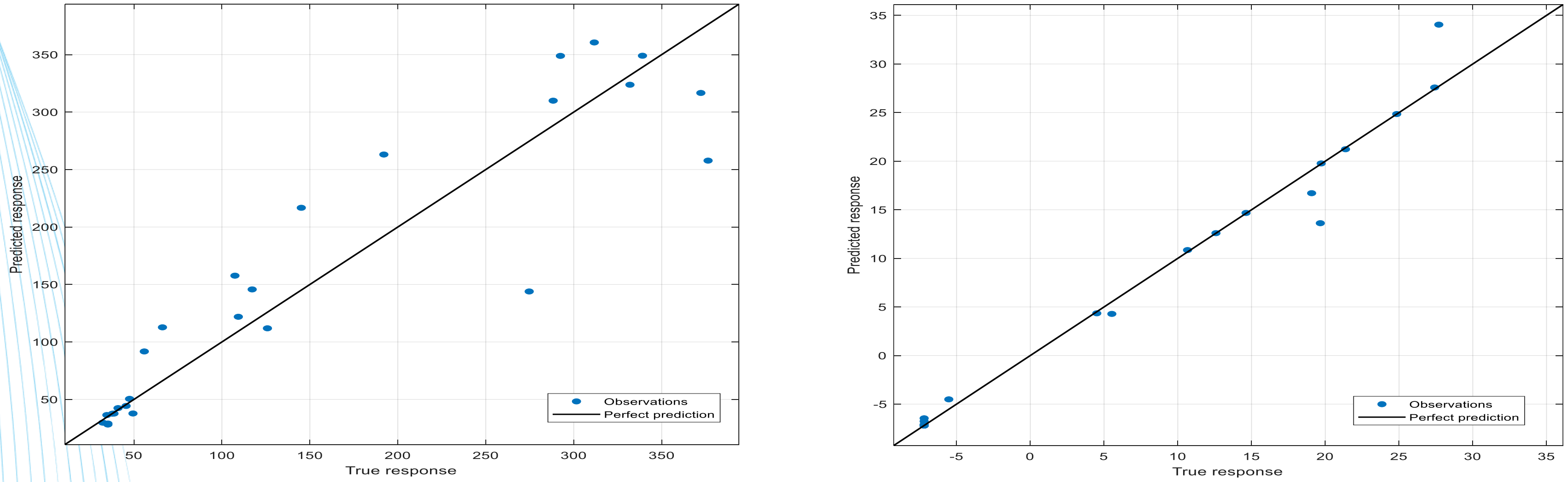
The three-layered neural network of MATLAB was employed, considering the predictors of *D* and *Q*. The output vector can be computed as follows:

where, ***p*** = predictor vector, ***a*** = response vector, ***W*** = weight matrix, ***b***= bias vector, ***IW*** = predictor weight matrix, and ***LW*** = layer weight matrix.



$a^1 = f^1(IW^{1,1}p + b^1)$ $\quad$ $a^2 = f^2(LW^{2,1}a^1 + b^2)$ $\quad$ $a^3 = f^3(LW^{3,2}f^2(LW^{2,1}f(IW^{1,1}p + b^1) + b^2) + b^3)$

Figure 6. Scheme of the three-layered neural network.



Validation and testing for Hmax and Hmin

achieving high accuracy: R^2 0.97 (*Hmax*) and 0.98 (*Hmin*) during testing

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4. Conclusions

- The integration of machine learning (ML) into hydrotransient modelling offers a powerful tool for enhancing operational safety, improving system design, and streamlining decision-making in fluid transport networks. The methodology demonstrates how data-driven techniques can complement traditional engineering approaches, providing fast, interpretable, and scalable solutions to complex hydraulic challenges.

- By leveraging ML algorithms, engineers can train models to recognise complex nonlinear relationships between input variables (such as for flow rates and pipe diameters) and critical outcomes (such as extreme pressure). This not only accelerates the modelling process but also provides access to predictive tools, allowing operators and designers without advanced mathematical knowledge or training to make informed decisions.

- Scalability is another key advantage. Once trained, ML models can be deployed across diverse pipeline configurations and operational scenarios with minimal recalibration. This is particularly valuable in large-scale water distribution networks, industrial fluid systems, or pump or hydropower infrastructures, where real-time monitoring and rapid decision-making are essential.

- Ultimately, the fusion of ML with hydrotransient modelling represents a forward-looking approach that blends computational efficiency, paving the way for smarter, safer, and more sustainable fluid transport solutions.

Thank you for your attention

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