



Turbine Health Analytics and Operational Optimisation

AI-based cavitation detection, impeller health diagnosis and market-aware hydropower scheduling

Bhavya Maheshwari

AI & Optimisation Modeller, Easy Hydro Solutions

Date: 8th September 2026 · Location: Brussels



This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101122167.

The problem

Vapour bubbles form and collapse inside the machine and the collapse energy erodes the impeller and shakes the casing

1 Local pressure drops

Off-design flow, part load and low suction head drop the local pressure below the fluid's vapour pressure.

2 Vapour bubbles form

Cavities nucleate near the impeller eye and along the leading edges of the blades.

3 Bubbles implode

Moving back into a higher-pressure region, the bubbles collapse violently and release shockwaves.

4 Erosion + vibration

Repeated implosions pit the blade surface and excite the structure — broadband vibration, noise, and resonance risk.



Fig. 3 — healthy vs damaged PAT impeller (iAMP-Hydro test rig)

Why it matters now

- Grid flexibility means more off-design and start-stop operation, so more time in cavitation-prone regions
- Wear changes blade geometry: imbalance and measurable efficiency loss
- Detecting it early is a maintenance and safety question, not only an efficiency one



Cavitation leaves a measurable signature in the vibration

Instrumented pump-as-turbine rig — condition monitoring under controlled cavitating and non-cavitating flow

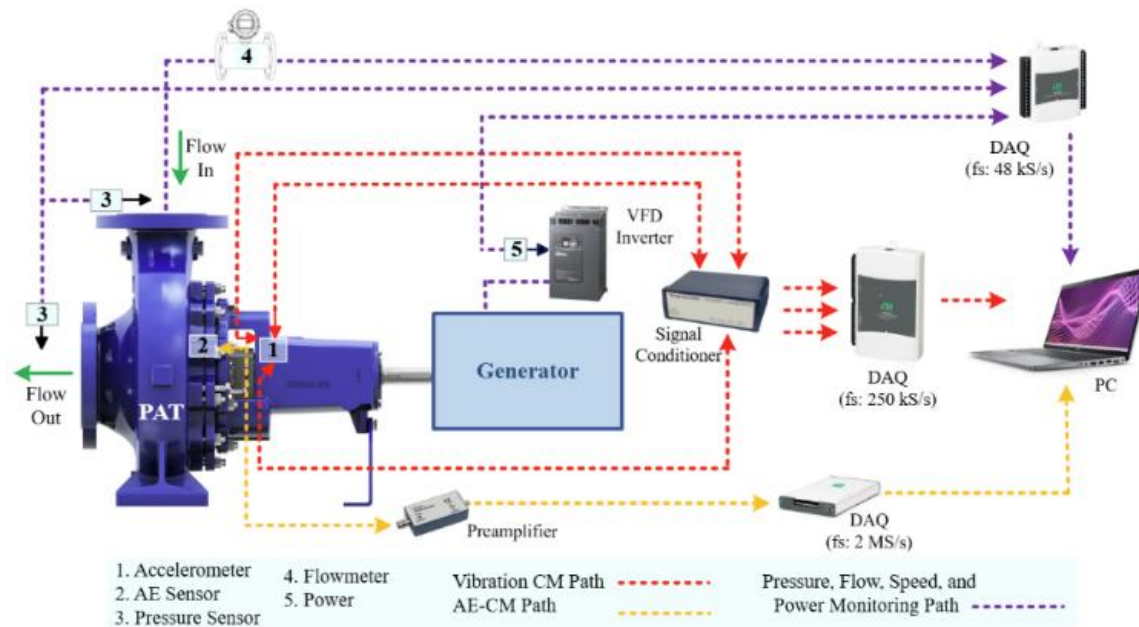


Fig. 1 — condition-monitoring set-up on the PAT test rig

The horizontal channel carried the clearest cavitation signature of the three axes — larger fluctuations, higher variability and more frequent high-magnitude spikes — so all spectral analysis uses that channel.

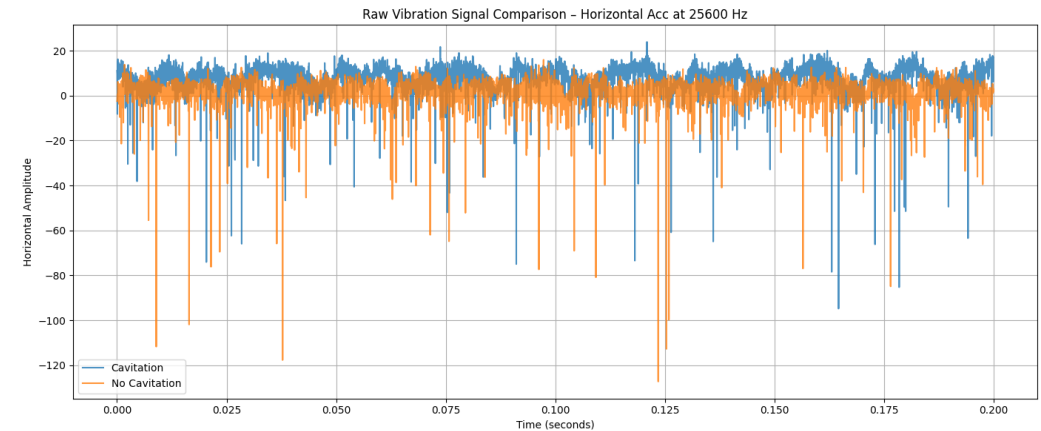


Fig. 4 — raw horizontal acceleration, cavitation vs no cavitation

- KSB Etanorm pump-as-turbine, 5.5 kW generator, grid-synchronised at 1500 rpm
- Three ICP accelerometers on the casing; vibration sampled at 25.6 kS/s
- Bypass valve stepped in 2.5° increments to sweep hydraulic operating regimes
- Cavitation labelled visually through a transparent viewing pane

Data Processing

A compact, physically interpretable pipeline — the same feature set serves both cavitation detection and impeller health diagnosis

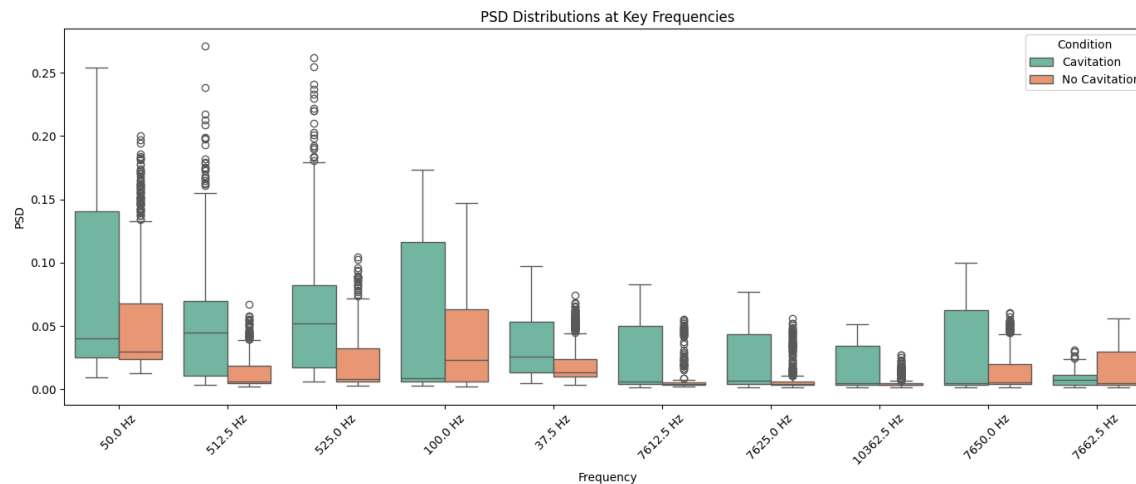
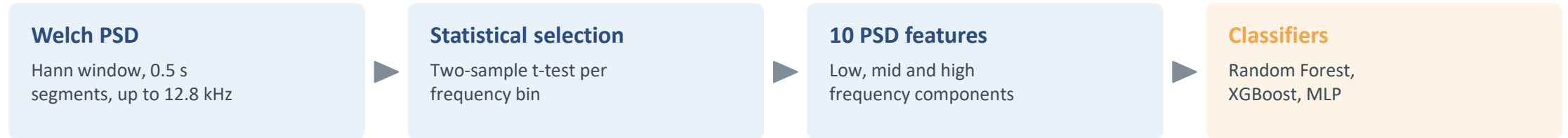


Fig. 5 — PSD magnitudes at the ten selected frequencies, cavitation vs no cavitation

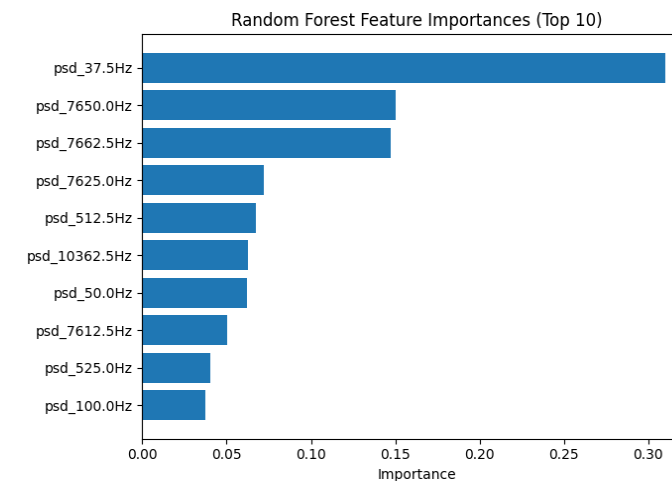


Fig. 8b — Random Forest feature importance

Models Random Forest (300 trees, depth 20, balanced class weights, grid search on macro-F1) · XGBoost (randomised search, early stopping) · MLP (10–64–32–2, Adam, standardised inputs) · Interpretability: feature importance, partial dependence and LIME

Results — cavitation detection

Binary classification on held-out test data (712 vibration segments)

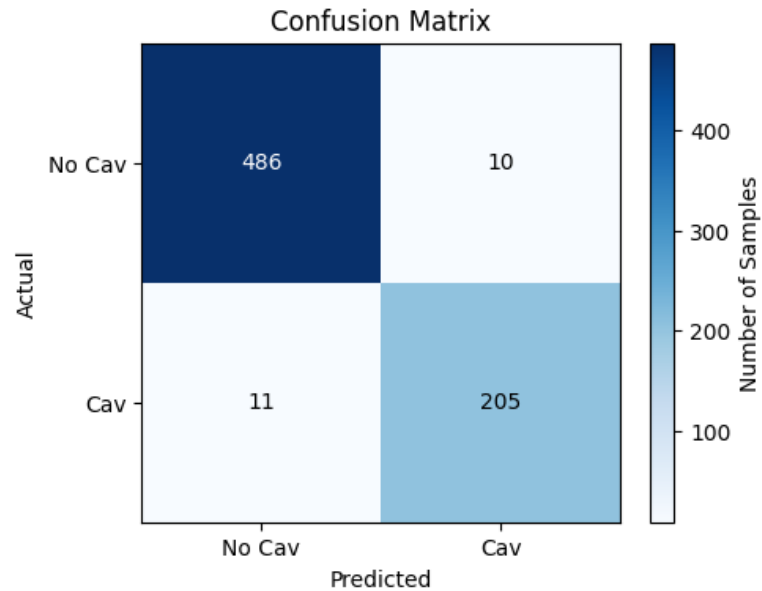


Fig. 8a — Random Forest confusion matrix

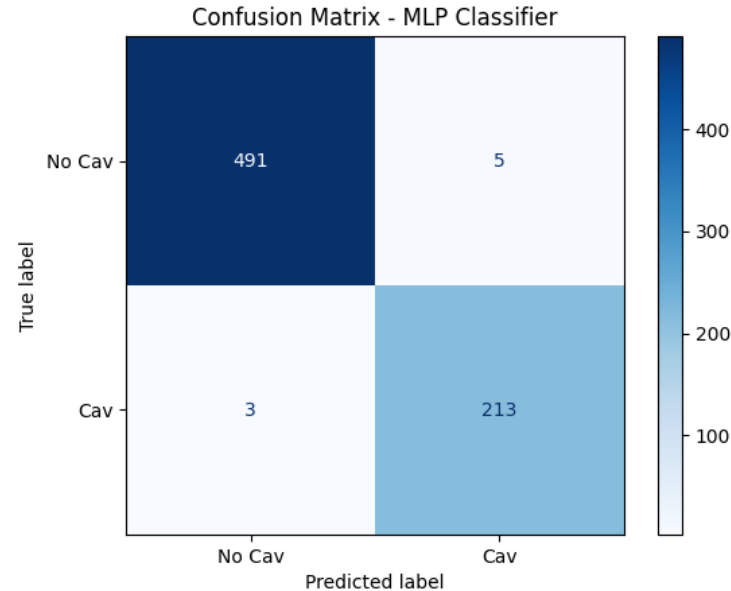


Fig. 11a — MLP confusion matrix

97.1%

Random Forest accuracy

99.0%

MLP accuracy

Random Forest

macro-F1 0.965 · ROC-AUC 0.997 · 21 of 712 segments misclassified

MLP

macro-F1 0.99 · 8 of 712 misclassified · smooth loss convergence, no overfitting

Errors are not random: both models miss in the same overlap region, where weak cavitation inception and turbulent but healthy flow produce almost identical spectral signatures. LIME confirms the MLP separates the classes on 37.5–100 Hz turbulence components and the 7.6–10.4 kHz collapse band.

Results — impeller health diagnosis

Baseline three-class classification, and the link between health state and hydraulic efficiency

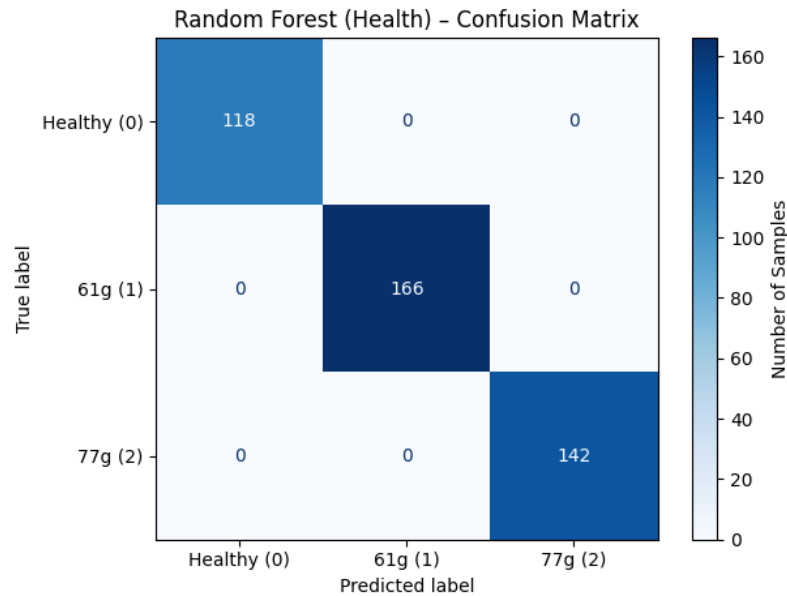


Fig. 13a — Random Forest health confusion matrix (cavitating flow)

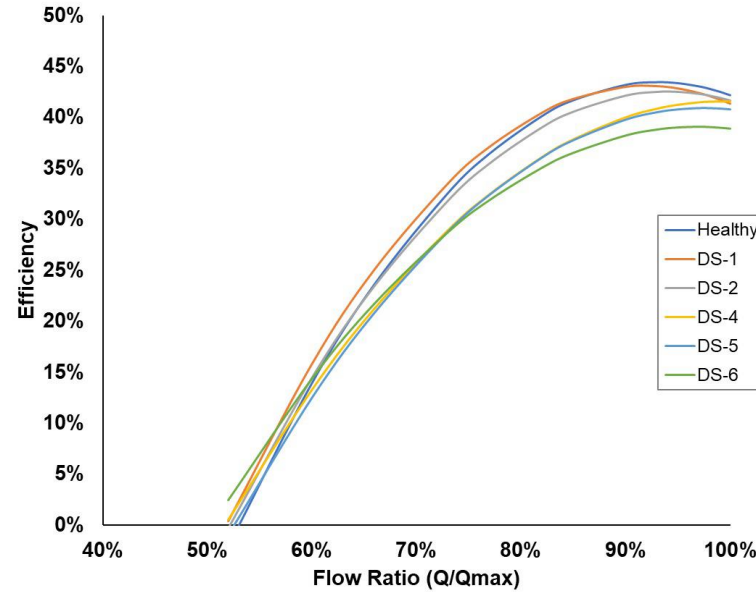


Fig. 25 — efficiency curves across the damage states

The efficiency curves fall in damage-state order: cumulative mass loss from 61.6 g (DS-1) to 186.1 g (DS-6) produces a progressive downward shift, most visible at high flow ratio. The health states learned from vibration are therefore not just statistically separable — they correspond to real lost hydraulic performance.

100%

RF & XGBoost, cavitating

99.8%

RF, non-cavitating

Classes: healthy (0) · 61.6 g loss (1) · 77.6 g loss (2)

Under cavitation both ensembles separate all three states with no misclassification. Without cavitation, Random Forest makes 2 errors in 976 samples and XGBoost none.

Discriminative bands shift from 7.6 kHz (cavitating) to 512–525 Hz and 10.4 kHz (non-cavitating).



Results — seven-stage staging and cross-condition robustness

Extending to seven degradation levels, and testing on operating conditions the model has never seen

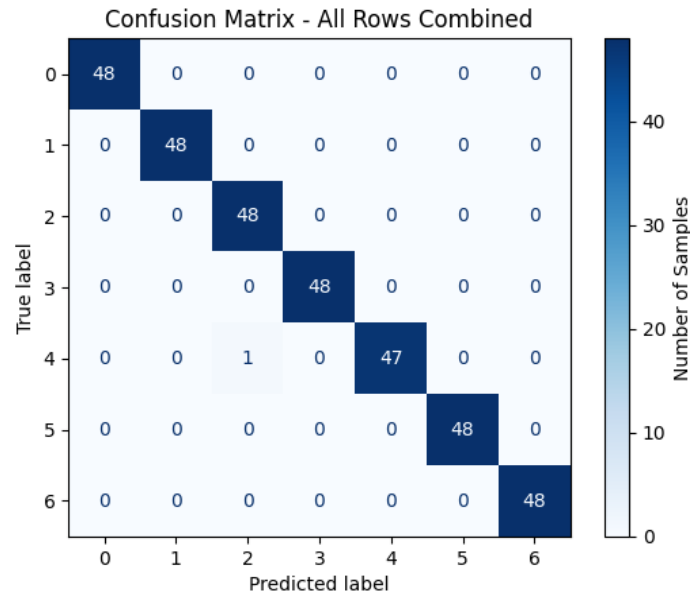


Fig. 21 — seven-stage confusion matrix (cavitating, pooled)

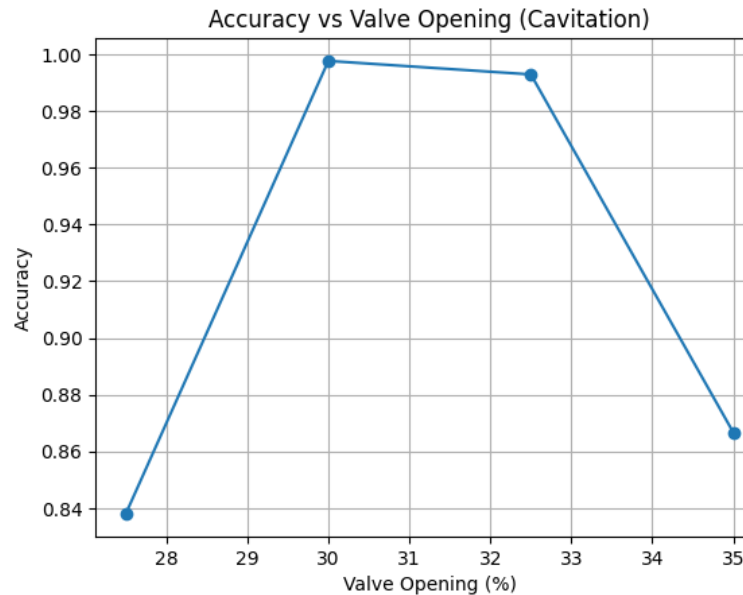


Fig. 19 — accuracy on the held-out valve opening (cavitation)

Reliability depends on the operating point, not only on the model. A standard random train–test split exposes the model to every regime during training and overstates field performance; holding out an entire hydraulic regime gives the number a flexible plant will actually experience.

1 error

Pooled 7-stage accuracy, cavitating

92.4%

Mean across held-out valve settings

Cross-operating-condition test

Train on every valve setting but one, then test on the excluded one. Accuracy is 99.8% and 99.3% at intermediate openings, but 83.8% at 27.5% and 86.7% at 35%.

Without cavitation the spread is wider still: 0.76 to 0.95 across valve settings, because the high-frequency collapse signature is absent.

Extreme states (DS-0, DS-6) stay accurate in every regime; confusions are between adjacent stages.



The optimisation tool — from plant data to a generation schedule

D11.2: a modular decision-support layer between the data management layer (iDML) and the operator interface (iDOL)

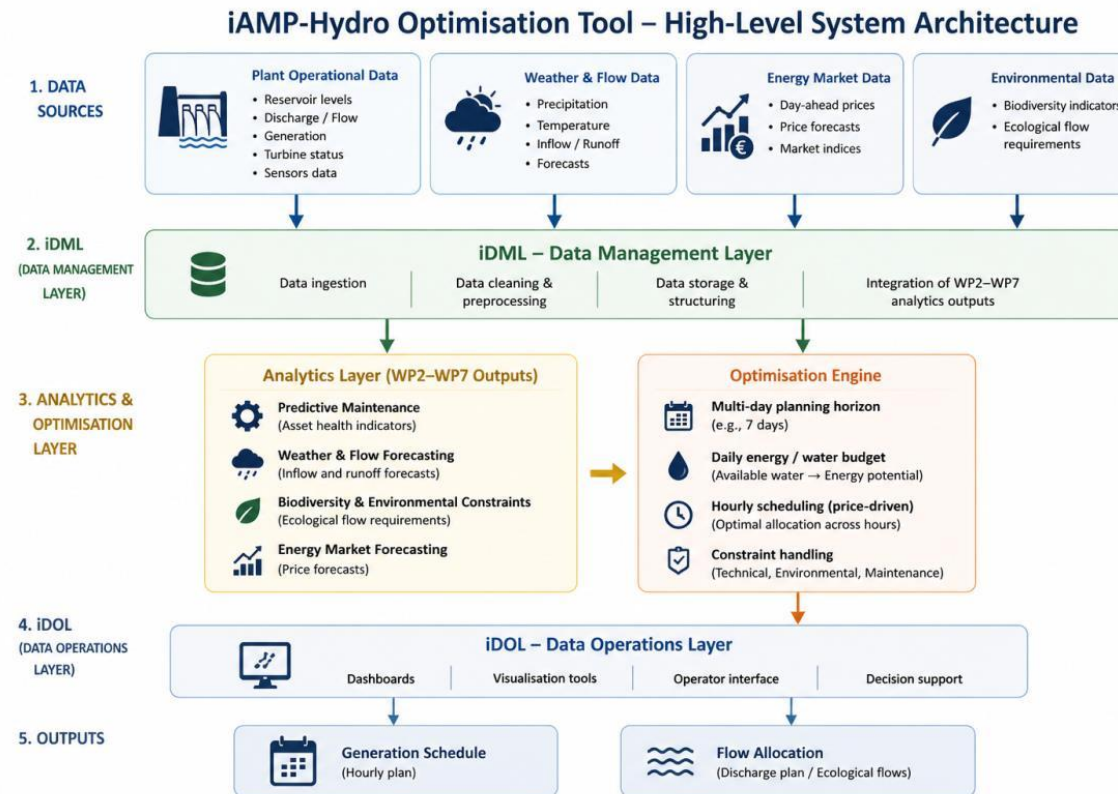


Fig. 1 (D11.2) — high-level architecture of the iAMP-Hydro optimisation framework

Objective

$$\max \sum P_t \cdot E_t - \lambda \sum |q_t - q_{t-1}|$$

Maximise revenue against the forecast hourly price, minus a ramping penalty that keeps the schedule mechanically realistic.

Decision variable

Hourly turbine discharge $q_t \in [0, q_{\max}]$ over a rolling 7-day horizon

Constraints

- **Water balance** — daily turbine volume $\leq$ available budget
- **Cavitation-aware** — safe flow 50–84% of $Q_{\max}$; part-load region 40–50% avoided; minimum head 36.4 m
- **Environmental** — site limits from NORCE (WP5): production cap, downramping limit, ecological flow
- **Hydraulic & plant** — flow, head and capacity limits from operational data
- **Ramping** — smooth transitions between consecutive hours

Two demonstrations — Asomata (Greece) and Bermejales (Spain)

The same framework produces two different operational strategies, depending on each site's water availability and constraints

Asomata HPP — Greece

Rolling 7-day market-aware scheduling on forecast water and energy · 16–22 July 2025

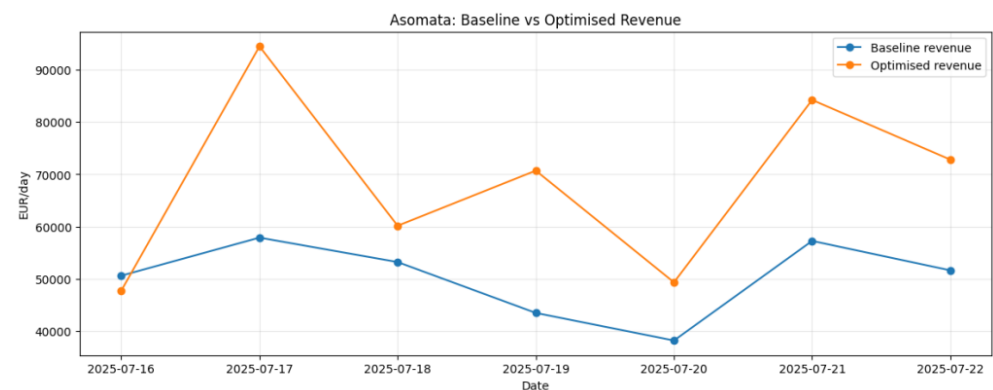


Fig. 6 (D11.2) — daily revenue, baseline vs optimised

	Baseline	Optimised
Energy	3511.37 MWh	3511.77 MWh
Revenue	€352,315	€479,436
Water	35.01 hm ³	35.01 hm ³

+36% revenue (+€127,121) on the same water and the same energy — the gain is entirely in when generation happens.

Bermejales HPP — Spain

7-day constrained allocation, irrigation-driven availability · 25–31 July 2025

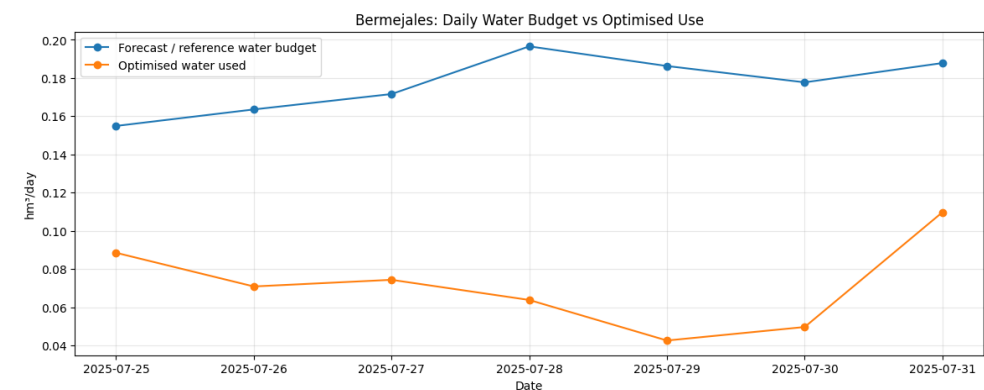


Fig. 9 (D11.2) — daily water budget vs optimised use

	Baseline	Optimised
Water	1.2386 hm ³	0.4995 hm ³
Energy	89.37 MWh	32.75 MWh
Revenue	€3,297	€2,420

59.7% of the water saved — only 40.3% of the budget used. Lower revenue in-window, but the water is kept for a later one.





Thank you

Vibration-based cavitation detection and impeller health diagnosis, and a market-aware optimisation tool that respects cavitation-aware and environmental operating limits.

Bhavya Maheshwari · maheshwarib@easyhydrosolutions.com

Easy Hydro Solutions Ltd. · iamp-hydro.eu