ACOUSTIC-VIBRATION ANOMALY DETECTION AND LOCALIZATION AT A PUMP-TURBINE

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Abstract. Pumped-storage plants provide the flexibility renewable grids demand, and their machines bear the cost in frequent mode changes and wear. Monitoring rests on vibration and plant data, with airborne acoustics unproven at full scale. We propose an alternative approach: healthy behavior modeled per operating mode from unlabeled data, deviations reported with calibrated confidence, and direction recovered by an array. A five-day analysis of a 295 MW machine, validated by observed impacts, defines the regularities and the limits our approach faces.

1. Introduction

The energy transition is transforming the demands that power grids place on hydropower. Wind and solar generation are volatile, and pumped-storage plants absorb that volatility, starting, stopping, and reversing far more often than their design era assumed. Each mode change between turbine (TU), pump (PU), phase-shifter (PH, synchronous-condenser), and standstill (ST) operation loads the machine with hydraulic transients, and the literature on transient-fatigue identifies start-stop cycles as a dominant consumer of Francis runner life [1, 2].

Condition monitoring relies on two pillars, vibration analysis (ISO 20816-5 [3], which is surveyed in [4]) and plant operating data. Both are well-established, and both have blind spots: industrial accelerometers roll off near 3.7 kHz, below the frequency-band where cavitation radiates most of its energy, and both observe the machine from fixed points with no spatial information. Microphones invert these properties: they capture the full audible frequency band, mount without contacting the machine or interrupting operation, and an array of them embeds direction. Yet, airborne acoustic monitoring of full-scale hydraulic machines remains barely characterized: no standard addresses it, and systematic multi-day field baselines are absent, so claims about its value rest largely on assertion.

This paper replaces that assertion with measurement, in a systematic baseline study of a dense acoustic-vibration array on at Rodundwerk II in Montafon, Austria, a 295 MW pump-turbine. The measurement[1] consisted of 5 days, about 38 hours of 9-channel audio (50 kHz) and 6-channel vibration (10 kHz), roughly 137,000 one-second windows in every

[1] Demonstration video: https://youtu.be/rneahOnLRUg

operating mode. It included both PH rotation directions, two load sweeps and all mode transitions, all healthy.

Inducing a fault in a live 295 MW machine is neither possible nor desirable, so we do not make a fault-detection claim. Instead, we detect and localize *controlled acoustic sources* against logged ground truth, and establish the healthy baseline that any anomaly claim depends on, how stable the acoustic identity is, how far one day's model carries, and how large a deviation the array detects.

To the best of the authors' knowledge, this is the first multi-day, full-scale *airborne* acoustic baseline of a pump-turbine across every operating mode, and its contributions are the following.

- We answer *how airborne acoustics contributes* over vibration and plant data, and we *ground-truth the array's localization*: against 180 hammer strikes at logged positions in two machine states, bearings land within a $\pm 20°$ sector (median $2.5°$), resolve in height, and every strike is detected while the machine pumps (Sections 4.5 and 4.6).
- We determine the *detectability limits* of an airborne array on a full-scale machine, calibrated per feature, mode and decision latency under a pre-stated validity rule, which fix the deviation any fault-detection claim must exceed (Section 4.4).
- We characterize the drift of the healthy state that is the main challenge to monitoring these machines, and formulate three *candidate principles* for when a baseline stays valid, offered as hypotheses for replication (Section 4.3).

2. Related Work

Vibration and plant data. Condition monitoring of hydraulic machines is based on shaft- and bearing-vibration analysis, standardized for hydro sets in ISO 20816-5 [3] and surveyed for Francis turbines in [4]. On an operating plant the limiting factor is rarely sensor noise but the spread of the healthy state across operating points. Normal-behavior models have been fitted to pump-turbines under extended operation [5], and per-regime baselines with extreme-value thresholds validated on running plants [6], all read from fixed points and none reaching the band where cavitation is loudest.

Acoustics of hydraulic machines. Cavitation has an established detection literature built on structure-borne acoustic emission and immersed hydrophones [7], and the geometric tones of a Francis machine are well understood [4]. Airborne, in-hall measurement with a microphone array on a full-scale unit is by contrast almost absent, its value asserted rather than shown on a multi-day field record. Our own earlier work compared acoustic anomaly-detection models for pumped-storage plants [8], but on a single short record, leaving open how they hold up across days.

Acoustic localization. Locating a source with a microphone array in a reverberant enclosure is a classic problem, solved robustly by steered-response power with a phase transform [9], yet ground-truthed localization inside a running powerhouse has not been reported.

Learning-based novelty. Outside hydro, unsupervised anomalous-sound detection is an active benchmark field whose domain-shift editions [10] reproduce in the laboratory the drift we measure in the field, and the structural-health-monitoring lesson [6] is that operational variability, not sensor noise, governs detectability. This paper fills that gap with an airborne, array-based, multi-day baseline, honest about drift and ground-truthed in localization.

3. Design

3.1 Method

We treat monitoring as one-class novelty detection on healthy data. We fit a baseline per operating mode on healthy windows (a one-class SVM on standardized log-features as reference) and re-check every transfer claim under an isolation forest, a quantile box and a distribution distance, so no conclusion relies on one detector's threshold geometry. Alarm thresholds are conformal, per load-regime bins (Mondrian conformal prediction [11, 12]): a held-out calibration sample sets a designed 5 % per-window false-alarm rate, and the detector abstains where calibration is thin or the operating point leaves the trained region. Window dependence makes the finite-sample guarantee approximate, so the block bootstrap carries the primary uncertainty.

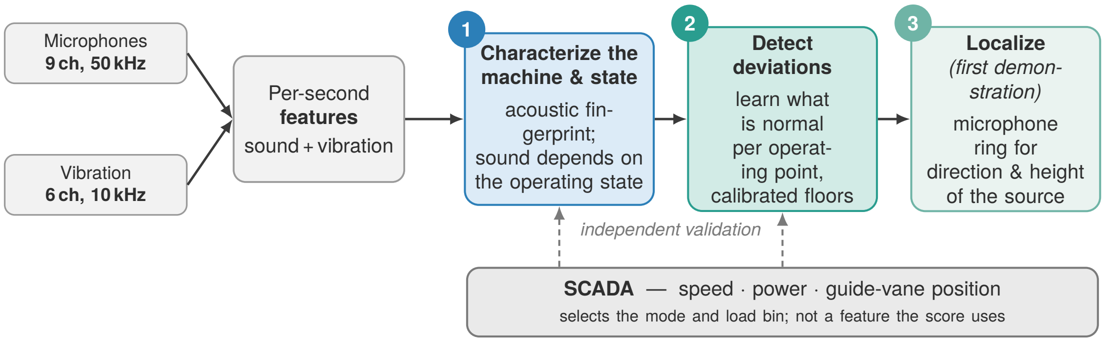


Figure 1: Data-ingestion and detection pipeline. A per-mode one-class baseline and a conformal, load-binned threshold turn them into a novelty score, with SCADA supplying the mode and operating point that gate the model.

Detectability is quantified by injection, meaning that a controlled gain (dB, both signs) is applied to one feature of held-out healthy windows, and MDD_{90} is the smallest deviation detected in 90 % of that set (thousands of windows at 1 s, about one hundred blocks at 60 s). The single-feature injection is conservative, and floors are reported only where the baseline reproduces its design false-alarm rate. Hypotheses formed on one result are tested on held-out data and reported regardless of direction, and the term pre-registration is reserved for the next-campaign predictions (Sections 4.6 and 5).

3.2 Data ingestion

The monitored machine is the 295 MW reversible Francis pump-turbine of Rodundwerk II (rated head 354 m, 375 rpm, 7 runner blades, 20 guide vanes, 16-pole generator). We used 9 free-field microphones (50 kHz, 10 Hz–20 kHz) that were strapped to the protection rail: four at the generator level (0, 90, 180 and $270°$, $r{=}2.40$ m, pointing up) and five at the turbine level 0.52 m below ($r{=}2.28$ m): the same four azimuths facing the guide vanes, plus one at the bottom pointing down (cf. Figure 3). Two tri-axial accelerometers at $180°$, one at each level, give six vibration channels, and the two $0°$ positions await extension cabling. Plant operating data (SCADA, 30 channels at 10 Hz) accompanies four of the five days.

Each one-second window yields time-domain statistics, spectral lines at the geometric fre-

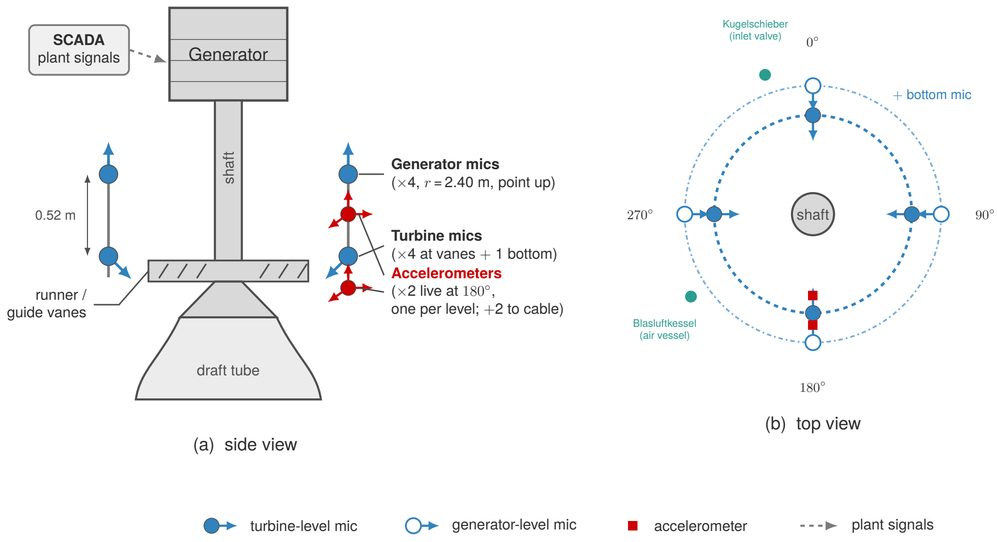


Figure 2: Sensor geometry. Side view (a) and top view (b) of the array: 9 microphones on two levels (4 at the generator level facing up, and 4 at the turbine level facing the guide vanes plus 1 at the bottom) with 2 tri-axial accelerometers at 180° (one at each level), and SCADA plant signals (radii not to scale).

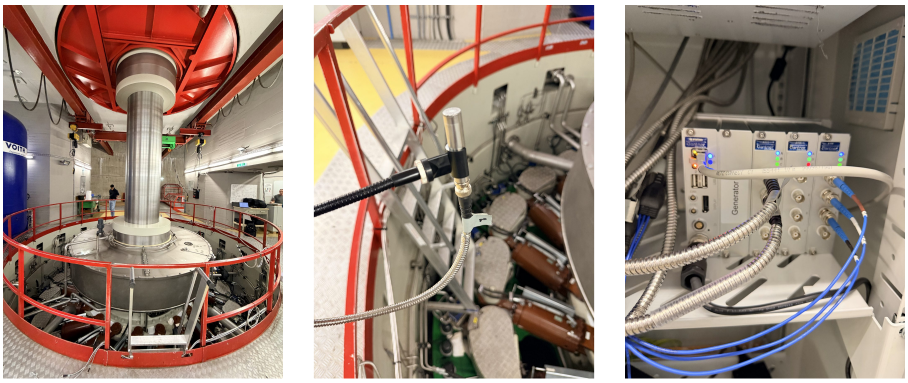


Figure 3: The system in the field. Left: the generator shaft with the machine open, showing the rail-mounted, non-contact installation. Center: a free-field microphone clamped to the protection rail at the turbine level. Right: the Gantner acquisition system.

quencies (shaft 6.25 Hz, blade pass 43.75 Hz, magnetic 100 Hz, vane pass 125 Hz), band energies, order-domain and cross-channel quantities. Corpus analyses use a 13-feature summary, and SCADA gives the mode and operating point that gate the baseline and its load-binned threshold (Fig. 1). The corpus covers five days: 25 June (turbine and pump), 27 June (pump and pump-direction phase shifter, without SCADA), 29 June (turbine, pump and phase shifter in both rotation directions, three start types, and the longest pumping block at 5.6 h), 30 June (pump and turbine), and 1 July (a full day with all modes and every transition type). The SCADA-less day was labeled to the minute from the microphones and is excluded from every label-dependent claim. Neighbouring one-second windows are strongly dependent, so all uncertainty is computed over 12-minute blocks and day-level folds, never over window counts.

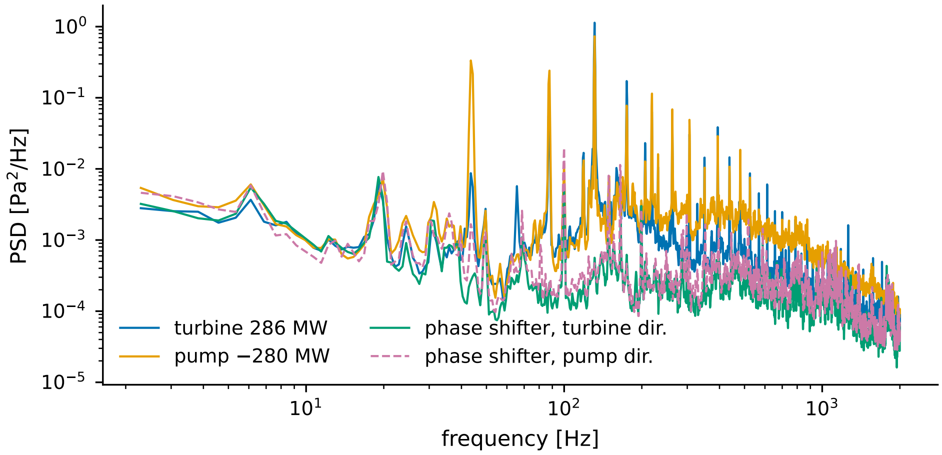


Figure 4: The four operating-mode signatures from a single day (29 June), including the phase shifter in both rotation directions.

4. Evaluation

4.1 System deployment

The array (cf. Fig. 2) ran on the machine across all campaign days and every operating mode, acquired *in situ* on the Gantner system (cf. Fig. 3) without contacting the machine and without an outage. Developed with the plant operator and not integrated into plant control, the array records alongside the regular operation on selected windows, and every result here comes from offline analysis of those recordings.

4.2 Acoustic identity

Each mode has an distinctive spectral identity (cf. Fig. 4). Within a day, modes separate from sound alone almost perfectly. Where plant data exists, a deterministic rule on valve position, speed and power gives the same labels for free. The acoustic value is independence, shown on the SCADA-less day, whose timeline came from the microphones alone.

The tonal architecture follows the geometry and reflects rotor-stator interaction between the runner and the guide vanes [4]. The pump blade-pass line (43.75 Hz, seven runner blades) is the most reproducible element: 27 to 28.5 dB signal-to-floor on all five pump days, on both sides of the two-epoch instrumentation break identified below. The epoch step moved signal and floor together, so the *ratio* is epoch-invariant while absolute levels are not: principal claim (i) in its concrete form. The 100 Hz generator line (16-pole machine) is present in every mode, direction and day at 9 to 15 dB, an electromagnetic reference measured acoustically, and the 125 Hz vane-pass line tracks load in turbine mode.

In phase-shifter operation, the inlet valve is closed and the runner spins in air: the hydraulic vibration band collapses by three orders of magnitude, its level set by rotation direction ($+47\,\%$ in turbine direction) and day-stable within 1 to 2 % per direction. Every PH period is a quiet generator observation window.

Load response is a machine constant (cf. Fig. 5): absolute levels shift 1 to 8 dB between days. Because two curves monotone in load correlate by construction, we quote the correlation of *detrended* curves: median $r{=}0.90$ (IQR 0.83–0.97) across features and day pairs, above the 95th percentile of a label-permutation null (0.73, raw $r{=}0.96$).

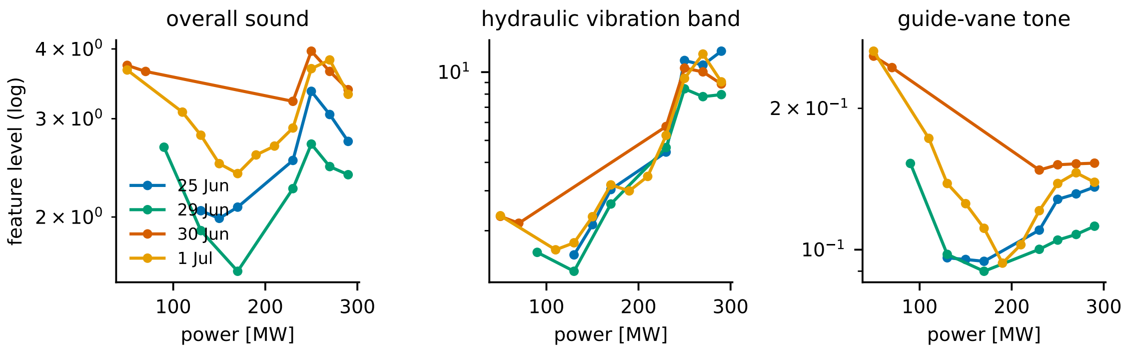


Figure 5: Feature-vs.-load curves for four turbine days: the shapes repeat (detrended $r=0.90$) while absolute levels shift.

4.3 Healthy variability and transfer

Within a run. At constant load within one run the healthy signature drifts for hours: a detector calibrated on the first hour of a 6.3 h block reaches 43 % false alarms in its second hour and 99 % by its fourth. The drift recurs: the vibration fundamental moved with the same sign in all five analyzed blocks and the spectral centroid in four of five (suggestive, not significant, $n=5$). A model trained across one *complete* warm-up transfers to the next run at 3 to 14 % and fails exactly where the machine leaves its trained range: claim (iii) in action.

Eliminations. We tested four explanations against plant data and rejected each. Overall level fails because level-free ratios drift equally, and reservoir level fails completely. Net head explains within-run drift (hour-two false alarms drop from 24 to 9 %), yet *worsens* every cross-day transfer. Time of day: a held-out directional test finds no consistent effect (28.3 vs. 29.4 % under one model, 78.7 vs. 69.8 % under another). Temperature is the surviving hypothesis and is absent from the export: our standing measurement request. Normal-behavior models on operating plants [6] anticipate this as they need explicit environmental compensation and re-referencing.

Across days. Static one-day baselines transfer from 4.9 % (1 July $\rightarrow$ 30 June, at the 5 % design rate) to 88 % for turbine and to 100 % for pump and phase shifter across an epoch boundary (cf. Fig. 6). The ordering is robust across four detector families. Every added sophistication tested (operating-point conditioning, level-free ratios) *worsened* transfer: claim (ii). Features divide into a stable class (1–3 dB worst-case day shift) and a drifting class (3–8 dB), prescribing two alarm-threshold regimes.

Two epochs. The pump matrix shows exact block structure: {25, 27 June} and {29, 30 June, 1 July} transfer within blocks (best cell 2.0 %) and fail between them. The likely cause is instrumental: microphone levels stepped $+1.1$ to $+2.6$ dB between 27 and 29 June while broadband vibration moved under 0.2 dB, which is not consistent with a machine or water-path change. Inferred from a single transition and not yet checked against a calibration log, the signature “microphones step, vibration flat” is a candidate sensor-chain diagnostic, though a change in the acoustic environment would leave a similar trace.

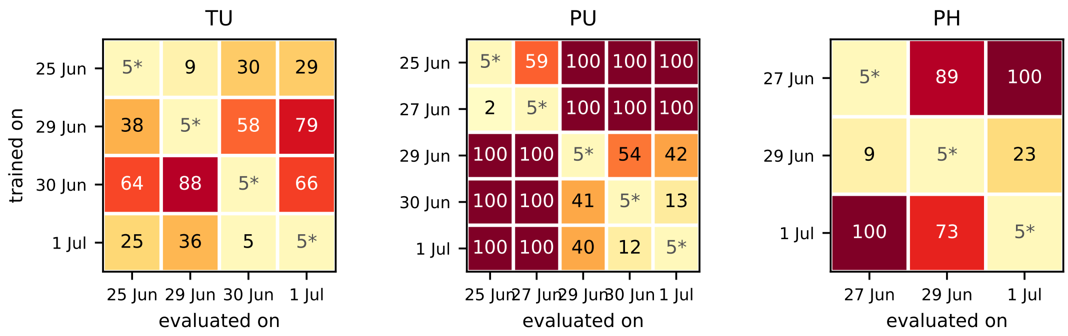
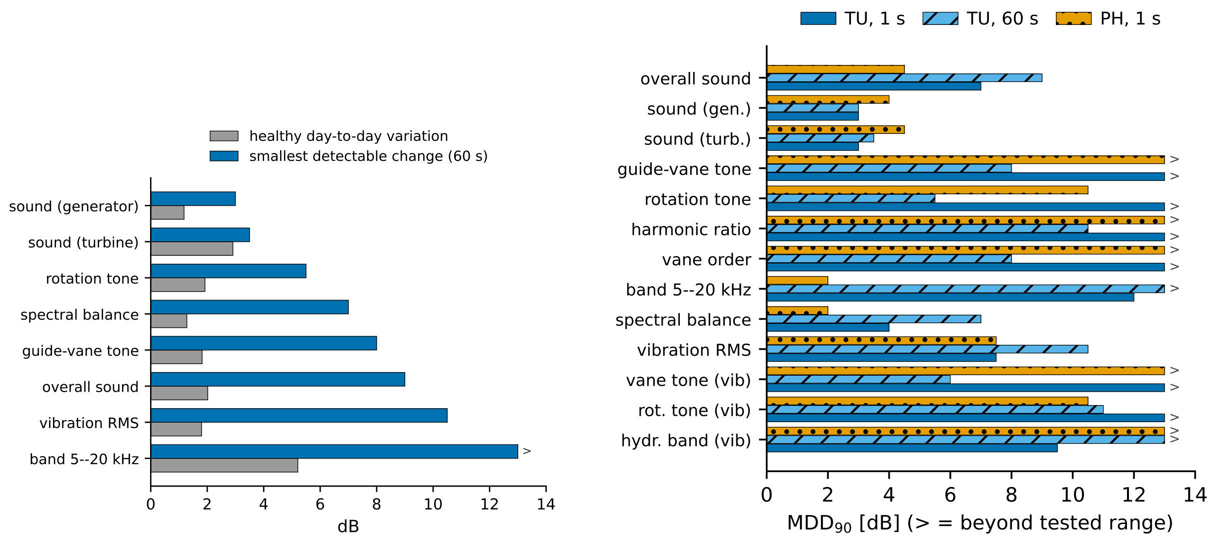


Figure 6: Day-by-day transfer of static baselines (false alarms on healthy data, matched load, own-day 5 % by design).



(a) (b)

Figure 7: Sensitivity of the array. (a) The smallest detectable change (60 s tier) sits above healthy day-to-day variation for every feature. (b) Detection floors (MDD_{90}) by feature, integration tier, and operating mode.

4.4 Detectability and transitions

Floors. Broadband levels are caught at 2.5 to 3.5 dB within one second. Individual machine tones are blind at one second but become observable at 5.5 to 8 dB with one-minute averaging. The quiet phase shifter reaches 2 to 2.5 dB in the microphone-exclusive 5–20 kHz band (cf. Fig. 7). At the one-minute tier every quotable floor exceeds that feature's own healthy day-to-day variation (cf. Fig. 7). Per the quotability rule, the pump floor (baseline failed its design rate) and standstill (too few recorded windows) are excluded. The one-minute tier is feasibility-grade ($n \geq 20$ per bin), and the in-sample check passes conservatively (4.0 vs. 5 %).

Transitions. The dataset holds three physically distinct start types, including a converter-driven turbine start: spin-up in air behind a closed valve, a 37-minute PH hold, then the valve opening onto the spinning machine (-36 MW water-rush transient). The starting converter is repeatable in the SCADA record: across 85 starts logged between 1 June and 1 July, spin-up durations agree within 3 s and peak currents within 3 A. Each start class can carry a learned reference shape, accepted in hydro life-expectancy practice from as few as two

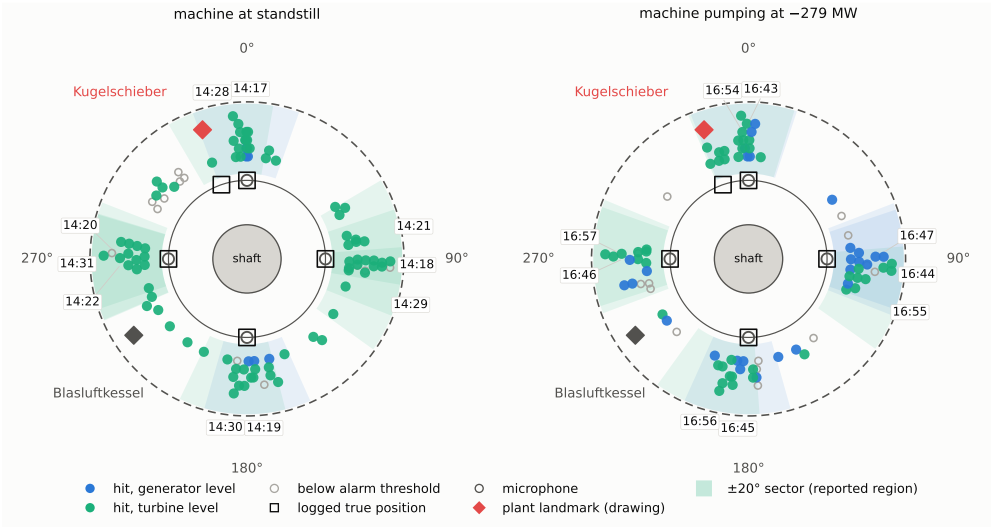


Figure 8: Ground-truth localization on 8 July, the hall seen from above in both machine states. Every hammer strike is placed on its measured bearing and each located event is reported as a $\pm 20°$ sector (shaded) rather than a point. Video available: https://youtu.be/rneahOnLRUg

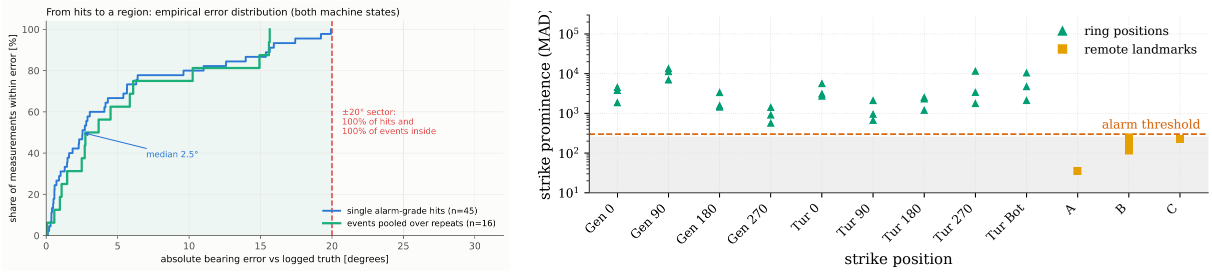
instances per scheme [2] on the transients that dominate runner fatigue [1]. Settling is history-dependent: about ten minutes after a 5.6 h pumping block versus under 90 s the same day.

4.5 Modality comparison

The two modalities are complementary, which is the point of fusing them. At a matched feature budget with day-level cross-validation over the five days, vibration and acoustics recognize the operating mode about equally well (both near 95 %), and acoustics does so with no plant integration at all: the SCADA-less day was labeled from the microphones alone. Each then adds what the other cannot. Acoustics reaches uniquely the band above the 3.7 kHz accelerometer limit, where the quiet phase shifter still shows a 2 to 2.5 dB floor, and its nine-microphone geometry gives a *direction* that no single accelerometer can (§4.6). Vibration keeps the structure-borne path, and the plant's efficiency index, stable to 0.6 % across four days at rated load, remains the slow-degradation channel that acoustics leaves untouched on healthy data (partial correlations ≤ 0.06). The value we report is the fusion: sound and vibration, time-synchronized, together identify the machine's state and localize a source.

4.6 Anomaly detection and localization

A fault is neither present nor wanted in a live 295 MW machine, so we test detection and localization on a controlled, repeatable source at positions logged by hand. On 8 July 2026 we struck a soft-faced hammer on an aluminium plate, a broadband, repeatable and harmless source, at twelve fixed positions, the nine microphone locations and three plant landmarks (one beside the *Kugelschieber*, the main inlet valve), and in a walk around the guide-vane circle, all repeated at standstill and while pumping at -279 MW, 180 strikes in all. Localization uses two physically independent readouts, the loudest-microphone energy balance and an SRP-PHAT timing estimate across the sample-synchronous ring, with the two-ring level difference giving the height.



(a) (b)

Figure 9: Localization ground truth, both machine states pooled. (a) Bearing-error distribution against the logged truth. (b) Detection under load.

Azimuth. Against the logged truth the energy readout (loudest microphone) and the SRP-PHAT timing readout agree, at a median bearing error of $2.5°$, with every located event inside a $\pm 20°$ sector (Figs. 8 and 9a). The guide-vane walk tracks the source around the full circle. Landmark A, struck beside the *Kugelschieber* and away from the sensor ring, pools to $15°$ from the valve direction taken independently from the sensor drawing, an acoustic bearing that lands on a mechanical landmark rather than on reverberant noise.

Height. The two microphone rings, 0.52 m apart, resolve the level: strikes at generator level arrive louder on the generator ring and turbine-level strikes on the turbine ring, the sign correct at 10 of 11 labeled positions.

Under load. Localization presupposes detection. All 27 ring strikes are detected while pumping, at prominence margins of 3 to $45\times$ over a threshold set for zero false alarms, and over 3.1 h of strike-free pumping that threshold raises only three benign transient events (Fig. 9b), the review queue such a tool should produce rather than noise. The accelerometers respond only to the structure-attached strikes, so the two modalities separate an airborne source from one coupled to the machine.

The direction survives the reverberant hall because localization is a timing estimate: the sample-synchronous Gantner acquisition and the phase-only SRP-PHAT weighting preserve the coherent direct-path arrival across the ring, and pooling repeated strikes suppresses the reflected-field scatter. Centimetre precision is not what a hall like this allows. A $\pm 20°$ sector is, ground-truthed here and pre-registered as the prediction for the next test.

Our experiments provide a first empirical basis for airborne acoustic monitoring of hydropower. The a full-scale machine with its acoustic identity, healthy variability and detection limits that were measured rather than assumed.

5. Conclusion

We presented the first multi-day, full-scale airborne-acoustic baseline of a pump-turbine. Our design treats monitoring as one-class novelty detection on healthy data, in which a baseline is fitted per operating mode, and its alarm threshold is conformal and binned by load regime. The baseline shows that every operating mode shows a distinct acoustic identity, and that the healthy state drifts between days without drifting arbitrarily, since the load response repeats as a machine invariant while only its calibration moves.

As a future work, we aim to compensate the day-to-day drift. The next campaign will ask whether the same reference (of Rodundwerk II) can be rebuilt at a second, smaller plant.

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