

A Reliability Digital Twin Architecture for Real-Time Fleet Monitoring and Predictive Maintenance of Hydrostatic Transmission Components

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ABSTRACT

As Digital Twins (DTs) are increasingly developed for Prognostics and Health Management (PHM), many published works remain conceptual, or rely solely on Data-Driven (DD) algorithms, that are difficult to deploy under fleet or industrial constraints. This paper proposes a reliability-centered DT architecture, specifically designed for fleet-level deployment with limited sensing, rare failures, and strong legacy knowledge.

The contribution lies in structuring and integrating heterogeneous estimation mechanisms, relying on physics-based lifetime models, Bayesian techniques for risk control of model updates, soft sensing, and with the adjunction of unsupervised anomaly indicators. The goal here is to have a coherent, explainable, and industrially deployable DT pipeline. Central to the framework is a two-level fusion strategy: (i) a centralized reliability fusion operating on cumulative damage, accelerated life testing (ALT) models and sparse failures, and (ii) decentralized embedded diagnostics, providing complementary health indicators under operational variability.

The architecture is demonstrated on hydrostatic transmission components using test-to-failure databases (DBs), accelerated life models, temperature soft sensing through Extended Kalman Filter (EKF) and neural networks (NN), and vibration-based anomaly detection/degradation quantifier via SOM-MQE. The paper explicitly addresses scalability, explainability, and statistical risk control, which remain open challenges in DT deployments for PHM. The proposed framework targets practitioners seeking DT implementations compatible with ISO-13374 logic, uncertainty guarantees, and industrial or fleet asset management constraints.

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1. INTRODUCTION

In the field of PHM, DTs promise a shift from reactive maintenance strategies toward predictive and reliability-centered decision-making. DTs have emerged as a central paradigm for bridging physical systems and their digital counterparts, through continuous data synchronization, modeling, and updating. In a recent publication, Xiao, Zhong, Bao, Chen, Bao and Zheng (2024) highlight the lack of systematic and integrated DT-PHM frameworks ; as well as the need for more structured and governed hybrid architectures. Penteado, Michalski, and de Souza (2025) provide a comprehensive overview of DT-PHM approaches, highlighting the diversity of modeling paradigms and the increasing reliance on data-driven techniques, while emphasizing on-going challenges in integration, standardization, and industrial deployment.

Simultaneously, major industrial companies—particularly in mechanical and hydraulic systems—benefit from decades of accumulated reliability knowledge, including failure mode analyses, ALT databases, and validated lifetime models. Leveraging this prior knowledge within a DT framework raises several methodological challenges ; notably the fusion of heterogeneous and time-varying operational data, the treatment of censored observations, and the scalability of computations at the fleet level.

This paper addresses these challenges by proposing a reliability DT architecture, fostering centralized fusion and embedded fusion mechanisms with:

- A reliability-oriented DT architecture benefiting from ALT data and Weibull-based lifetime models, for traceability and statistical risk control.
- A centralized, low computation fusion framework based on Weibayes inference, enabling fleet-level deployment under realistic industrial constraints, including censored data and limited onboard resources.

- A progressive architectural transition, from a baseline cumulative model DT toward a hybrid DD model integrating Bayesian filters and Deep Learning (DL). Particularly, a deployment of hybrid soft sensing methodology for thermal degradation assessment, combining Extended Kalman Filtering (EKF) and DL models within a unified Bayesian loop.
- A deployment for embedded health indicators through an original use of SOM-MQE as a quantitative degradation variable rather than anomaly detectors, suitable for long-term health tracking in operational environments, and capable of overriding the DT at different levels.

The proposed work addresses the following research questions:

- RQ1: How can a Digital Twin for reliability assessment be designed when only ALT databases and parametric lifetime models are available?
- RQ2: How can heterogeneous indicators (loads, cycles, temperature, vibration) be fused coherently under non-stationary operating conditions?
- RQ3: Under which conditions do the integration of machine learning (ML) and DL provide tangible benefits over purely model-based approaches?
- RQ4: How can explainability, traceability, and risk control be preserved in a DT integrating artificial intelligence?

The contribution of this work is therefore architectural and methodological.

2. RELATED WORK AND POSITIONING

This section positions the proposed work with respect to the state of the art in DTs for PHM. This contribution acknowledges gaps in developments to date and structures a framework to address them. The review of several scientific contributions points to: (i) the lack of documented DTs validated at fleet scale, (ii) the limited integration of reliability engineering practices, (iii) the limited governance of hybrid data-driven approaches, and (iv) the predominant use of health indicators as event-based anomaly flags.

From Conceptual DT Models to Deployment-Oriented PHM Architectures

Digital Twin concepts initially emerged from product lifecycle management and cyber-physical systems, emphasizing high-fidelity virtual representations for design and performance optimization, as described by Grieves and Vickers (2017) or Tao, Zhang, Liu and Nee (2018). More recent architectural extensions toward PHM integrated condition monitoring and prognostics, have been proposed through the concepts described by Lu, Liu, Wang, Huang,

and Xu (2020). Recent surveys consistently report that many DT-PHM implementations remain conceptual or limited to demonstrator-level studies, with rarely documented evidence of large-scale or fleet-level deployment, under industrial constraints such as sparse failures, heterogeneous usage profiles, and censored data.

Data-Driven and Reliability-Centered DT Paradigms

Jiao, Zhao, Lin, and Liang (2020) publication highlights that most DT-PHM approaches rely predominantly on DD techniques based on ML and DL, which achieve strong diagnostic or prognostic performance when large, representative datasets are available. Zio (2022) establishes that major challenges remain in uncertainty management, decision relevance, industrial deployment, calling for reliability oriented and risk governed frameworks.

Indeed, reliability-oriented models based on lifetime statistics provide traceability, probabilistic guarantees, and direct support for maintenance decision-making. To name a few, Meeker and Escobar (1998) and Nelson, (2004) provided detailed calculations, ALT model evaluations, demonstrations for risk evaluation in reliability topics, given the reference and the foundations they provided for modern reliability developments. However, reliability algorithms are often applied offline or only partially integrated into dynamic DT architectures. This contrast motivates DT designs that place reliability models at the core, while integrating DD components in a controlled manner.

Bayesian Updating, Hybrid Soft Sensing, and Health Indicators

As Bayesian inference mechanisms, including Weibayes updating, are well established in reliability engineering, especially for contexts with limited failures and censored observations (see Abernethy, 2006), their explicit integration as governing mechanisms within DT architecture remains limited, as described by Penteado et al., (2025). Hybrid approaches combining Bayesian filters for soft sensing and data-driven models for nonlinear estimation have been proposed without explicit links to reliability constraints or uncertainty control. This hybridization gap has been identified as a major challenge for the practical deployment of PHM systems by Fink, Nejjar, Sharma, Niresi, Sun, Dong, Xu, Wei, Bizzi, Theiler, Tian, Von Krannichfeldt, Ma, Garmaev, Zhang, and Zhao (2025).

Similarly, unsupervised learning techniques such as Self-Organizing Maps (SOM) are widely used in PHM, predominantly as threshold-based anomaly detectors, following the work provided by Kohonen (2001). Their exploitation as continuous degradation indicators suitable for long-term health tracking and reliability trending remains relatively underexplored in literature.

Positioning of the Proposed Work

The proposed work is positioned within a reliability-centered Digital Twin paradigm, in which lifetime models, statistical inference, and probabilistic risk control constitute the foundation of the architecture. The DT is constrained by established reliability models and test-to-failure knowledge, thereby ensuring traceability and decision-level consistency. Within this framework, data-driven and learning-based components are introduced progressively as complementary estimation modules, operating either under Bayesian governance at the central level, or as embedded, potentially autonomous indicators. Their role is to enhance state observability, nonlinear estimation, and sensitivity to emerging degradations. This hierarchical integration enables extensibility and explainability, while remaining fully compatible with established industrial PHM practices, and risk-based maintenance strategies.

3. RELIABILITY DIGITAL TWIN ARCHITECTURE

3.1. Architectural Principles

The proposed Digital Twin architecture is designed around three guiding principles: statistical evaluation of the risk, industrial scalability, and progressive enhancement. The DT operates on a fleet of machines equipped with heterogeneous sensors and communication capabilities. Data are collected, transmitted, stored, and processed within a cloud-based infrastructure, while computation-intensive or latency-sensitive algorithms may be deployed on embedded hardware when they are available.

The proposed architecture emphasizes fleet-level central fusion, ensuring coherence between individual assets, ALT databases and enabling mutual shared learning from failure events.

Following an ISO-13374-compatible PHM logic, the proposed DT is structured around data acquisition, state assessment, prognosis, and advisory layers. Two complementary fusion levels are defined:

- Centralized fusion, operating on aggregated fleet data and reliability DBs.
- Embedded fusion, operating locally on machines to capture fast or poorly modeled phenomena

The DT is updated periodically (hourly for state estimation, weekly for reliability updates), ensuring consistency between operational monitoring and long-term reliability assessment.

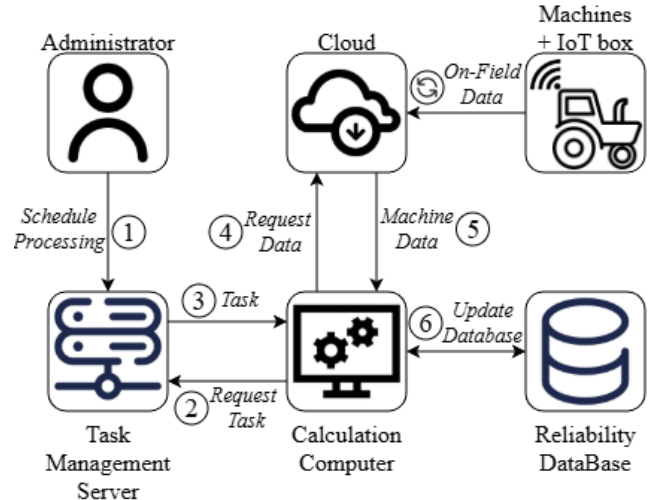


Figure 1. General DT Architecture

3.2. Centralized Fusion Baseline

The novelty of the architecture lies in:

- The explicit separation between cumulative reliability backbone and adaptive diagnostic overlays.
- The use of Weibayes as a DT core update mechanism, enabling statistically controlled learning from suspensions and failures. The fusion relies on cumulative damage or degradation indicators derived from load, cycle, and temperature histories. Acceleration Factors (AFs) are computed with respect to reference ALT conditions, enabling the normalization of heterogeneous operating profiles.
- The definition of upgrade paths, allowing additional AI modules to be integrated without invalidating existing reliability guarantees.

This baseline architecture favors robustness and explainability over algorithmic complexity and constitutes the foundation upon which more advanced techniques can be integrated.

3.3. Architecture Description

To develop the architecture, a Proof of Concept (PoC) was developed based on recommendations of ISO 13374 *Condition Monitoring and Diagnostics of Machines*, and previous publications such as Vogl, Weiss, and Donmez, (2014).

The DT is organized following a specified framework frequency. In the PoC every signal is chunked through hourly frames, and the lifetime calculations are refreshed within this hourly periodicity. However, the DB update is synchronized through an initial weekly period, since the core lifetime

models usually predict thousands of potential lifetime hours at the beginning.

3.3.1. Data Collection

Each machine in the fleet is equipped with an IoT databox that acquires measurements from the machine’s CAN network, as well as from additional sensors (pressure, temperature, speed) installed specifically for the DT. The databox collects data in real time at frequencies between 10 Hz and 50 Hz. The data is transmitted almost immediately via a cellular network to cloud servers, with end-to-end latency typically below five minutes.

3.3.2. Cloud Storage

The cloud infrastructure provides persistent storage and retrieval of data originating from IoT databoxes. It exposes two web APIs (Application Programming Interfaces): One receives data from devices and stores it in S3 based file storage. One processes client requests by decoding, resampling and returning the relevant data on demand.

3.3.3. Reliability Database

The reliability DB centralizes all information required for digital twin computations. It contains general component data, machine descriptions, and digital representations of the physical components installed on each machine. It also stores the outputs of reliability analysis.

3.3.4. Automatic Data Processing

The final architectural component orchestrates the workflow: a Task Management service responsible for automated DB updates.

Server

Administrators configure, for each machine component, parameters such as update frequency (from hourly to yearly), the component identifier in the DB, processing priority, and the corresponding cloud data path. Using this configuration, the server generates a queue of tasks for execution by a calculation client. When a client connects, it affects the task with the highest priority.

Calculation Client

A dedicated software component running on a computation machine retrieves tasks from the server, downloads the associated data from the cloud, preprocesses and cleans the data, performs the necessary calculations, and writes the results back to the DB. When a task is done, the calculation client sends confirmation to the server the work is done, which allows the server to track which tasks are done and which might have crashed.

4. CENTRAL FUSION WITH MODEL BASED ALGORITHMS

4.1. Problem addressed

A key challenge in fleet PHM is exploiting heterogeneous duty cycles without storing or replaying full mission profiles. Usual data can contain a subset of pressures, forces, speed, flow and temperatures. These are metrics that can be measured with sensors that are not necessarily complex or expensive to implement. The fleet monitored contains the same product, or product similar enough to be merged with respect to lifetime, and load (e.g. same product family, same hot spot locations, same failure mechanisms and failure modes...). In general, this is possible with the knowledge of an ALT and a lifetime model. The compression of operational history is performed through forms of damage normalization or equivalent life metrics, preserving statistical meaning while enabling adaptability to load variations, or fleet product heterogeneities.

4.2. Accelerated Life and Cumulative Damage

For example, in the domain of contact fatigue of rolling elements, one possibility is to reduce or average, for each signal, a quantity such as any form of timely normalized damage or pseudo damage :

$$D_{\text{norm}}(t) = \text{mean} (\text{Coef}(T) \cdot \text{Stress}(t)^m \cdot \text{Speed}(t)^s) \quad (1)$$

Where :

- Coef(T) represent a coefficient depending on the temperature T and other parameters. Friction coefficient is a possible example.
- m and s are power exponents, assuming an inverse power law life model.
- The quantity is associated with a probability of failure (e.g. B10 life)

If a component had to fail in the field, it should be marked as so (e.g. F instead of suspended S), in the evolving Test DB, then removed from the monitoring.

Table 1. Monitored elements and transformed quantities for revolution depending degradations

Component	Accumulated Time	Acceleration Factor	Status (F/S)
1	$\tau_1(t)$	$AF_1(t)$	F
2	$\tau_2(t)$	$AF_2(t)$	S
3	$\tau_3(t)$	$AF_3(t)$	S
...			
n	$\tau_n(t)$	$AF_n(t)$	S

The AF of an i^{th} component, can be assessed with respect to its lifetime model as the ratio of timely normalized (pseudo) damage as :

$$AF_i(t) = \frac{D_{\text{norm}, i}(t)}{D_{\text{norm}, \text{Ref}}} \quad (2)$$

The AF column in Table 1. is a mix of ALT data and field evolving data. The AF and the accumulated time columns are time dependent. The quantities evolve from the very beginning until the current point in time. The capacity to aggregate each quantities from the origin, can be calculated with an odometer in the case of the cumulated time, or with extensions of Eq. (1).

In the event of cumulative models from counting techniques, a model bounded between 2 quantities makes sense. It is particularly the case with Palmgren-Miner damage accumulation, 0 meaning a brand-new component, and 1 a theoretical failure associated with a certain probability.

In such case it would make sense to estimate the AF according to the cycle ratio:

$$AF_i(t) = \frac{N_{\text{Ref}}}{N_i(t)} = \left(\frac{\text{Stress}_i(t)}{\text{Stress}_{\text{Ref}}} \right)^m \quad (3)$$

Where :

- N_{Ref} represents the lifetime reference cycles possible at a reference load, and associated to a probability of failure (e.g. B10 life)
- N_i represents the lifetime cycles possible under the current equivalent load of the i^{th} component and associated with the same probability of failure.

For fatigue following counting process such as described in Fig 2. the associated DB can be reworked as in Table 2.

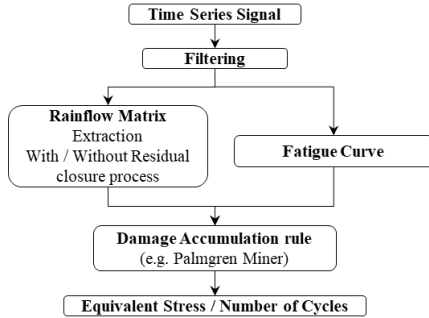


Figure 2. Equivalence of damage and Rainflow process overview

On the topic of number of cycles, there are capital letters and non-capital letters used in the paper. The capital letters represent the number of cycles to failure, associated with a probability of failure (usually 10% with hydraulic components), while the non-capital letters represent the exact accumulation of cycles. Further developments and refinements on the specific topic of fatigue, damage accumulation and counting techniques can be retrieved through the work achievements and book contribution of Dowling, N. E. (2012).

Table 2. Monitored elements and transformed quantities for cyclic loading degradations

Component	Equivalent Cycles at reference load	Status (F/S)
1	$n_{\text{eq}1}(t)$	F
2	$n_{\text{eq}2}(t)$	S
3	$n_{\text{eq}3}(t)$	F
...		
n	$n_{\text{eq}n}(t)$	S

4.3. Weibayes Algorithm for fusion

The Weibull distribution is widely used to model the lifetime of mechanical and hydraulic components. In this paper, Weibayes inference is employed as a semi-Bayesian approach in which the shape parameter is fixed based on prior knowledge, while the scale parameter is updated from field data.

The Weibayes framework naturally accommodates censored observations and incremental updates, making it particularly suitable for fleet monitoring. By incorporating AFs derived from cumulative damage formulations, the DT continuously updates reference lifetime metrics, such as B10 or Bq lives, within evolving operating conditions. The central fusion process follows a Bayesian predict–measure–update loop:

- Predict: component life is extrapolated from reference ALT conditions using time-dependent AFs.
- Measure: accumulated operating time, cycles, and degradation metrics are monitored.
- Update: reference lifetime parameters are updated using Weibayes inference upon the occurrence of new failures.

This approach offers a pragmatic compromise between statistical rigor and computational efficiency, enabling deployment on large fleets with limited resources.

In one of its useful forms, and for a specific failure mode, Weibayes enable to assess (after fixing the shape β) the quantile life B_q , considering k failures and n monitored samples as:

$$B_q \text{ Proven} = \left[\ln \left(\frac{100}{100 - q} \right) \cdot \frac{2 \cdot \sum_{i=1}^n AF_i^{\beta_{\text{rev}}} \cdot \tau_i^{\beta_{\text{rev}}}}{\chi_{2(k+1)}^2; \text{Confidence}} \right]^{\frac{1}{\beta_{\text{rev}}}} \quad (4)$$

Or the number of cycles N_q associated with the probability $q/100$ to fail :

$$N_q \text{ Proven} = \left[\ln \left(\frac{100}{100 - q} \right) \cdot \frac{2 \cdot \sum_{i=1}^n n_{\text{eq}i}^{\beta_{\text{cyc}}}}{\chi_{2(k+1)}^2; \text{Confidence}} \right]^{\frac{1}{\beta_{\text{cyc}}}} \quad (5)$$

The development of this equation can be retrieved in a close form through “SIA – Handbook for Automotive Reliability – Assessment and Validation. Practical sheet 9: Reliability test calculation by the Weibayes methodology p 83”.

This initial deployment of the DT was performed through a mode-to-mode reliability estimate, therefore using Weibayes with Chi Square computation of the confidence limits. The DT focused on the prior knowledge of expected failure modes, that were of 2 in this PoC. This was driven by the sake of simplicity and a certain degree of conservatism in each failure mode B10 life assessment, when exposed to a reference load. Therefore, there are 2 shape parameters : one for revolution dependent degradation and another for cyclic torque reversals.

In the event where several failure modes would have a set of ALT database and reliable accumulated hours/cycles available, it makes sense to assess each product reliability under the assumption that best models the overall reliability. In the case of competing failure modes for example, the component reliability is :

$$R_{\text{component}}(t) = \prod_{i=1}^{\text{Nbre Modes}} R_{\text{mode } i}(t) \quad (6)$$

The assumption of Weibull distribution on each failure mode provides:

$$R_{\text{mode } i}(t) = e^{\left(-\frac{t}{\eta_{\text{mode } i}}\right)^{\beta_{\text{mode } i}}} \quad (7)$$

Table 3. Comparison of Bootstrap and MCMC for the evaluation of system reliability in a centralized fusion framework.

Parameter	Bootstrap	MCMC
Data Requirements	Small datasets	From small to complex
Model Complexity	Simple models	Simple to complex hierarchical models
Suspensions	Good handling	Great handling
Computational Time	Fast	Slow. requires checking several parameters : convergence, efficiency, shrink factor, autocorrelation...

At the central core, additional fusion of each failure mode reliability into a system assessment is feasible, through either Bootstrap, either MCMC or Monte Carlo computation. This is achievable thanks to the centralized fusion architecture.

In the specific field of MCMC or Monte Carlo computation for Reliability, Liu and Abeyratne, (2019), provide different examples where these techniques can help, especially on complex systems or multi-failure mode components, in particular chapters 6 and 7. For the MCMC checking of

simulation parameters, the book of Kruschke, (2014), provides detailed descriptions of the required parameters verifications for a good Bayesian MCMC computation.

4.4. Bayesian Inference principle: Predict – Measure - Update

The DT implements a closed Bayesian loop, where reference lifetimes are continuously refined as new censored or failed units are observed.

In the predict phase, the life of an i^{th} component is derived from a reference life as:

$$\text{Life}_{\text{pred}, i}(t) = \frac{\text{Life}_{\text{Ref}}}{\text{AF}_i(t)} \quad (8)$$

Eq. (8) is linked to a specific probability of failures $q/100$ with Eq. (9) , by considering the life reference as a byproduct of the reference scale η_{ref} :

$$B_{q \text{ Ref}} = \eta_{\text{Ref}} \cdot \left[-\ln\left(1 - \frac{q}{100}\right)\right]^{\frac{1}{\beta}} \quad (9)$$

The measure phase is perpetual in the DT. The measurement concerns the transformed $\text{AF}_i(t)$ and the accumulated time/cycles of each component $\tau_i(t)$ or $n_{\text{eq}i}(t)$, as described in Table 1. and 2. This measurement phase enables a primitive form of RUL evaluation through a formulation equivalent to:

$$\text{RUL}_i(t) \equiv \text{Life}_{\text{pred},i}(t) - \tau_i(t) \quad (10)$$

The update phase is performed through the Weibayes algorithm, adjusting the reference life to the calculated B_q life

$$\text{Life}_{\text{Ref}} \equiv B_{q \text{ Proven}} \quad (11)$$

Table 4. Comparison Bayesian & Weibayes for DT

Stage	Bayesian	Weibayes
Predict	Prior distribution on β and η	Weibull with fixed β_0 , unknown η
Measure	Likelihood from observed data	Number of failures, total accumulated time, AF
Update	Posterior distribution	Posterior estimation of η and any B_q derivative

For a specific failure mode, the shape parameter β is assumed constant, to keep consistent the hypothesis of non-modification in failure mode upon AF value, as long as it remains within acceptable ranges.

The cyclic mechanism inherent to Bayesian behavior occurs with the accumulation of time and failures. Non-negligible updates in lifetime values happen any time a new failure arises and gets uploaded to the database, as depicted in Fig 3.

4.5. Digital Twin Baseline Test

The test of the DT was performed following its capacity to predict, measure and update in a weekly manner. The prediction and measurement are rather straightforward if a cumulative damage/degradation model enables to link a duty cycle with an expected normalized damage or any equivalent metric. The AF can be assessed from the knowledge of the ALT model.

The update is the main cornerstone of the test evaluation. It follows the aggregation of the different duty cycles, and the increase in number of accumulated hours/cycles with the expected lifetime values (here expecting a B10 of the rotating elements in the 10,000 hrs range, and N10 around 80,000 cycles).

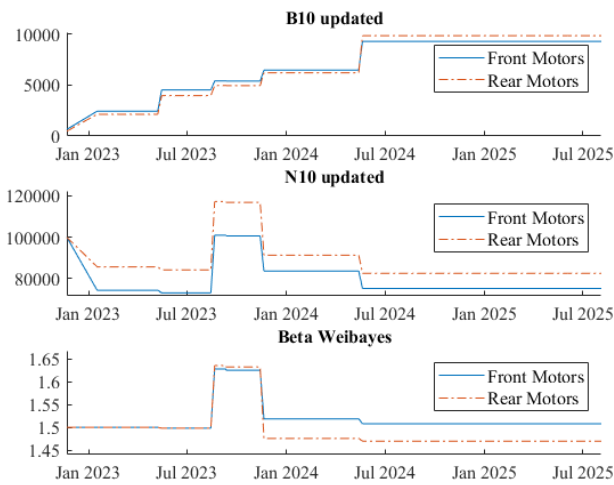


Figure 3. Update Test of the DT sequence with Weibayes

5. HYBRID EXTENSION THROUGH SOFT SENSING

5.1. Soft Sensing for Unmeasured Degradation Factors

Many key degradation drivers, such as internal temperature, are not directly measurable in operational conditions. Soft sensing is therefore required to extend DT and lifetime model applicability beyond instrumented variables :

- Model-based Bayesian filters like EKF, offering interpretability and physical consistency.
- DL models (FFNN, LSTM), presenting higher flexibility under complex nonlinearities.

While model-based methods ensure traceability, their performance may be limited by parameter uncertainty or unmodeled dynamics.

5.2. Deep Learning fusion in model based Soft Sensing

To mitigate prediction risk, provided that model uncertainty is explicitly quantified and monitored, and that DL models are validated under representative operating conditions, these

NN can be embedded within Bayesian estimation architectures as virtual sensors. Their outputs, associated with confidence intervals, are injected into state estimators, enabling real-time uncertainty propagation. DL models are particularly valuable as complementary components when physical parameters are uncertain, nonlinearities dominate, and edge deployment constraints apply. For instance, Choi, Jang, Cho, Moon and Kim. (2024) demonstrate the feasibility of edge-deployed DL-based virtual sensing, through PCA-based compression and autoencoder-based anomaly detection, while Bublil, Taal, Maljaars, Klein, Bortman (2024) provide physically grounded labeling approaches, based on load signals that could support the construction of reliable health indicators.

Overall, these approaches highlight the potential of combining virtual sensing and physically interpretable measurements, which can be fused within digital twin architectures to enhance robustness and decision support.

5.3. Temperature Soft Sensing

Temperature drives hydraulic system degradation through cumulative exposure above critical thresholds and cyclic thermo-mechanical variations. Reliable temperature estimation is therefore required prior to lifetime model updating. Temperature is slowly varying, spatially distributed, involving nonlinear quantities in their assessments. They are rarely measurable at critical locations (see Fig. 4). Traditional nodal thermal models require detailed parameterization and are difficult to deploy on embedded hardware.

When operational DB labelling hydraulic inputs to thermal responses are available, DL-based soft sensing allows estimation of internal temperatures at critical locations. After integration into a Bayesian framework such as Kalman Filters (KF), these estimates act as probabilistic measurements, ensuring consistent updating of degradation and lifetime models.

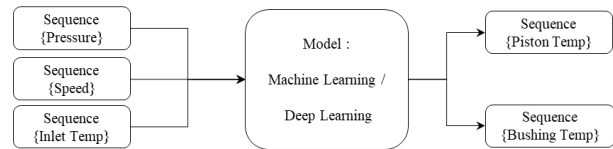


Figure 4. AI for temperature soft sensing of a hydraulic motor.

5.4. Core Model-Based AI

5.4.1. Example with the development of an Extended Kalman Filter for Internal Temperature Soft Sensing

With available physical knowledge and differentiable models, KF constitute strong candidates for soft sensing. As dynamic Bayesian estimators, they naturally support both temporal fusion and spatial state reduction. For temperature

estimation in rotating components, where thermodynamic behaviors are locally linearizable, Extended Kalman Filters (EKF) provide an appropriate formulation, by linearizing the state and measurement models around the current estimate. This requires the underlying system to remain locally observable and the estimation error to stay within a domain, where first-order approximations are valid. EKF-based temperature soft sensing has been successfully demonstrated on electric drives using indirect electrical and thermal measurements (Huang and Guehmann, 2014).

Similar approaches applied to hydraulic components have enabled reliable internal temperature estimation while reducing the thermal network dimension by a factor of 5 to 10 through nodal aggregation. In the present work, EKF-based temperature estimates are treated as probabilistic virtual sensors, whose associated uncertainty—accounting for both process noise and linearization effects—can be reinjected into degradation and lifetime models.

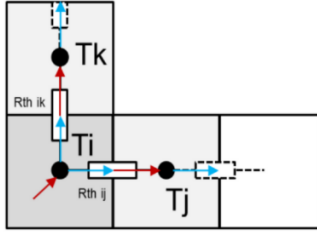


Figure 5. Nodal Modeling

The first Thermodynamic principle adapted to rotating hydraulic components is :

$$= \sum \frac{T_j - T_i}{R_{th_{conduction j, i}}} + \sum \frac{T_j - T_i}{R_{th_{convection j, i}}} + \sum P_i + \sum (Q \cdot \rho \cdot C_p) \cdot (T_j - T_i) \quad (12)$$

With :

- m the mass of the node element [kg]
- C_p the calorific capacity of the node element [$J \cdot kg^{-1} \cdot K^{-1}$]
- T_i the node temperature [K]
- T_j the temperature of any other nodes with conduction or convection or fluid transport heat exchange with node i [K]
- P_i heat generation with transfer through the node i . It can be the consequence of friction, for example
- $(Q \cdot \rho \cdot C_p) \cdot (T_j - T_i)$ represents fluid transport related to a flow going through the node i

- $\frac{T_j - T_i}{R_{th_{conduction j, i}}}$ represents conduction heat transfer between node i and other nodes j .
- $\frac{T_j - T_i}{R_{th_{convection j, i}}}$ represents convection heat transfer between node i and other nodes j .

Note : Radiated energy is negligible compared to other forms of energy and is therefore not considered in this paper.

The system that EKF solves can be expressed as :

$$\begin{aligned} X_{k+1} &= f(X_k, U_k) + w_k \\ Z_k &= h(X_k) + v_k \end{aligned} \quad (13)$$

With :

- X_k : state vector (node temperatures)
- f : prediction function depending on the state variable and the exogeneous inputs
- U_k : vector of exogeneous inputs (load, external conditions)
- w_k : process noise
- Z_k : measurement vector
- h : measurement function
- v_k : measurement noise

At first glance, process noises and measurement noises are assumed Gaussian with a mean of 0 :

$$w \sim \mathcal{N}(\mu = 0, \sigma^2 = Q) \quad (14)$$

$$v \sim \mathcal{N}(\mu = 0, \sigma^2 = R) \quad (15)$$

The state estimate vector X_k is equal, after discretization, at each time step k to :

$$X_k = \begin{pmatrix} T_1^k \\ T_2^k \\ \vdots \\ T_n^k \end{pmatrix} \quad (16)$$

The vector of exogeneous inputs is :

$$U_k = \begin{pmatrix} P_1^k \\ \vdots \\ P_p^k \\ T_{exogen 1}^k \\ \vdots \\ T_{exogen m}^k \end{pmatrix} \quad (17)$$

KF starts their process by an initialization of the state variables $X(t=0)$ and the Process Covariance matrix $P(t=0)$. Then Bayesian Inference mechanism of ‘‘Predict-Measure-Update’’ applies.

During the prediction at step k , both the state variables and process covariance matrix are evaluated :

$$X_k^- = f(X_{k-1}; U_k) + w_k \quad (18)$$

$$P_k^- = F_k \cdot P_{k-1} \cdot F_k^T + W_k \cdot Q_k \cdot W_k^T \quad (19)$$

- $F_k = \frac{\partial f}{\partial x}|_k$: Jacobian matrix of f , following the vector X given the time step k
- $W_k = \frac{\partial f}{\partial w}|_k$: Jacobian matrix of f , following the process noise vector W around 0 given the time step k
- P_{k-1} : previous step covariance matrix
- P_k^- : predicted process covariance matrix
- Q_k : process noise covariance matrix that is expressed with the Gaussian noise assumptions as :

$$Q_k = \begin{pmatrix} w_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & w_w \end{pmatrix}_k \quad (20)$$

The measurement phase assesses the quantity Z_k through the measurement function h . It grants in the update step an assessment of quantities such as the Kalman Gain, which yields in this case :

$$K_k = P_k^- \cdot H_k^T \cdot (H_k \cdot P_k^- \cdot H_k^T + V_k \cdot R_k \cdot V_k^T)^{-1} \quad (21)$$

- $H_k = \frac{\partial h}{\partial x}|_k$: Jacobian matrix of the measurement function h following the vector X given the time step k
- $V_k = \frac{\partial h}{\partial v}|_k$: Jacobian matrix of the measurement function h following the noise measurement vector V around 0 given the time step k
- R_k : measurement noise covariance matrix that is expressed with the Gaussian noise assumptions as :

$$R_k = \begin{pmatrix} v_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & v_v \end{pmatrix}_k \quad (22)$$

5.4.2. Test of the EKF

A set of complex duty cycles were concatenated to simulate different dynamic conditions for the machines, involving steady states values, back and forth and stop/start conditions.

The intention is to reach any enveloping values (e.g. min-max loads, max power, ...) to test the capacity of sensing critical temperatures, even in the harshest conditions.

The duty cycles were created with the purpose of error maximization, by focusing on dynamic conditions rather than steady state. Indeed, KF better correct errors in steady state conditions. The creation of such EKF to sense critical temperatures, where no sensor could be implemented, allow for a temperature RMSE below 10K in the test (see Fig 7.).

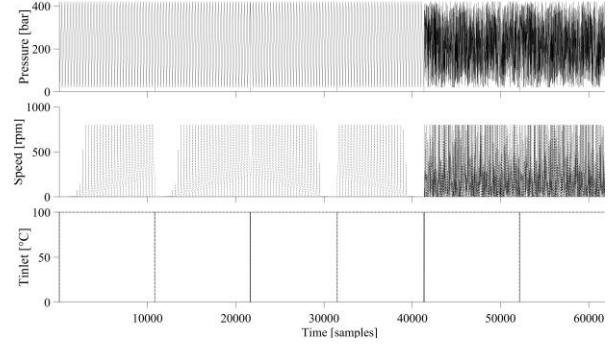


Figure 6. Subset for Thermal EKF Inputs for Test & Validation

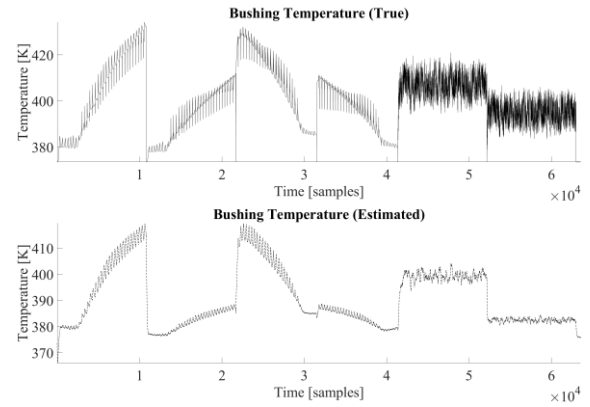


Figure 7. EKF Test & Validation bushing temperature predictions

One benefit of using KF techniques is the filtering effect of the estimated temperature, compared to the legacy (true) model. Another benefit is interpretability of the model, compared to DL models.

5.5. Aggregation of Deep Learning

When load inputs and corresponding temperature outputs are correctly labeled, DL provides an alternative soft sensing strategy, often complementary to model-based approaches. Specifically, NN capable of processing temporal sequences and embedding memory effects are well suited for temperature estimation in systems exhibiting inertia, delays, and nonlinear thermal couplings.

To illustrate this approach, two architectures were developed and trained using the same input set as the EKF-based estimator:

- Feed-Forward Neural Network (FFNN) augmented with memory by duplicating each input sequence with a moving average of past values.
- Long Short-Term Memory (LSTM) network, explicitly designed to capture long-term temporal dependencies.

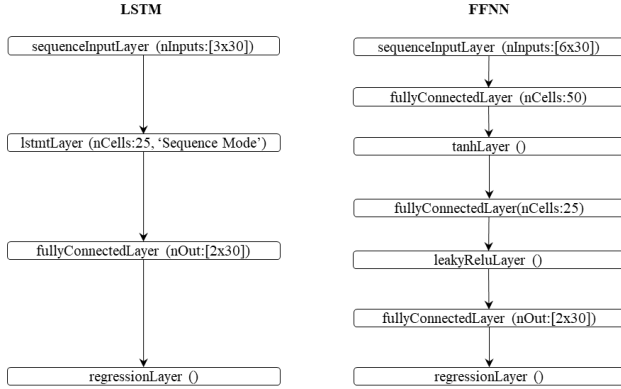


Figure 8. Parallel development of 2 NN with memory capacity.

Both DL models were trained and validated under test-bench conditions involving variable load profiles, including the presence of significant measurement noise.

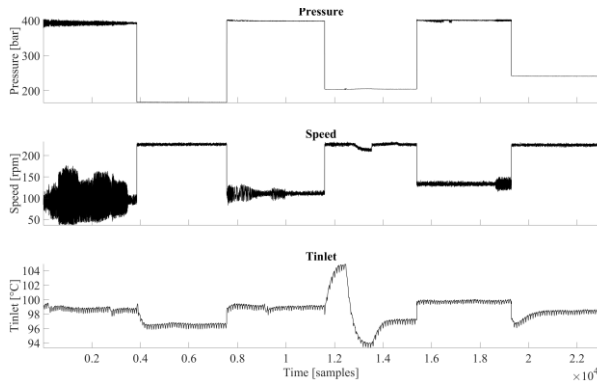


Figure 9. Subset for Thermal NN Inputs for Test & Validation

These NN demonstrated the ability to accurately predict internal temperatures at critical locations. Compared to EKF-based soft sensing, however, DL estimators may exhibit weaker intrinsic filtering properties, depending on the excitation dynamics, the memory depth, and the learning configuration. As a result, residual noise or bias can remain in the temperature estimates, motivating the fusion of multiple soft sensing techniques.

5.6. Fusion of DL-Based Temperature estimates

To reduce noise and mitigate estimation bias, the temperature predictions provided by the LSTM and the FFNN can be fused together. When both estimators rely on the same sensor set, their errors are potentially correlated, making Covariance Intersection (CI) an appropriate fusion framework. The variances of the two estimates can be approximated from their respective RMSE values as:

$$\text{Var}_{\text{LSTM}} = \text{RMSE}_{\text{LSTM}}^2; \text{Var}_{\text{FFNN}} = \text{RMSE}_{\text{FFNN}}^2 \quad (23)$$

The fused variance is then expressed as:

$$\text{Var}_{\text{fused}}^{-1} = \omega \cdot \text{Var}_{\text{LSTM}}^{-1} + (1 - \omega) \cdot \text{Var}_{\text{FFNN}}^{-1} \quad (24)$$

where $\omega \in [0,1]$ is a tuning parameter reflecting relative confidence in each estimator.

The fused temperature estimate becomes:

$$\widehat{\text{Temp}}(t)_{\text{fused}} = \text{Var}_{\text{fused}} \cdot (\omega \cdot \text{Var}_{\text{LSTM}}^{-1} \cdot \text{Temp}(t)_{\text{LSTM}} + (1 - \omega) \cdot \text{Var}_{\text{FFNN}}^{-1} \cdot \text{Temp}(t)_{\text{FFNN}}) \quad (25)$$

and the associated bilateral confidence interval is given by:

$$\text{Temp}(t) = \widehat{\text{Temp}}(t)_{\text{fused}} \pm z_{\alpha/2} \sqrt{\text{Var}_{\text{fused}}} \quad (26)$$

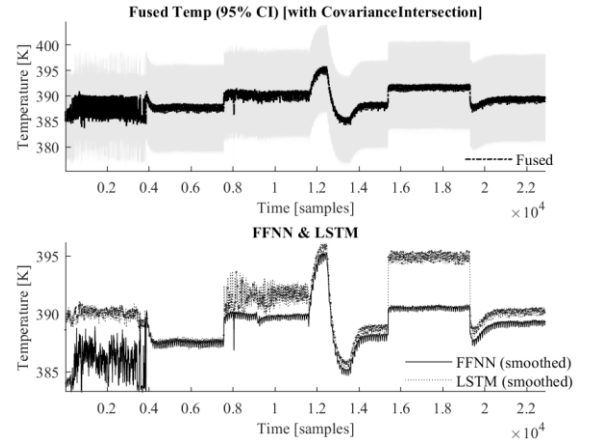


Figure 10. Fused estimation of temperature from LSTM & FFNN.

5.7. Hybrid Soft Sensing

While EKF-based soft sensing provides physically interpretable and uncertainty-aware estimates, its performance can degrade when model parameters are uncertain or when nonlinearities exceed the local linearization domain. Conversely, DL-based estimators offer higher flexibility but weaker physical interpretability. This motivates hybrid extensions combining model-based observers with data-driven virtual sensors (see Fig. 11).

Following the filtering structure of the thermal EKF, the DL-based fused temperature estimate can be introduced as an additional virtual measurement. Without recomputing the full EKF structure, this new measurement complements or replaces physical temperature sensors by adapting the measurement model $H_k = \frac{\partial h}{\partial x}|_k$, the noise mapping $V_k = \frac{\partial h}{\partial v}|_k$, and the covariance matrix R_k . This mechanism preserves the Bayesian “predict–measure–update” structure while extending observability at critical internal locations.

5.8. Thermal Degradation Digital Twin

The ability to combine multiple temperature soft sensing techniques allows for the reconstruction of a more reliable and risk-assessed internal thermal state. This capability is

essential for deploying temperature-driven ALT models within a reliability-centered DT.

Temperature estimates can be directly coupled with degradation laws such as Arrhenius-type models, commonly used to describe thermally activated ageing and creep mechanisms. The corresponding acceleration factor (AF) is expressed as:

$$AF \equiv e^{\left(\frac{E_a}{K_B} \cdot \left(\frac{1}{T_{ref}} - \frac{1}{T_i}\right)\right)} \quad (27)$$

- E_a : The activation energy in [eV]
- K_B : The Boltzmann constant
- T_{ref} : the reference temperature in [K]
- T_i : the temperature of component i in [K]

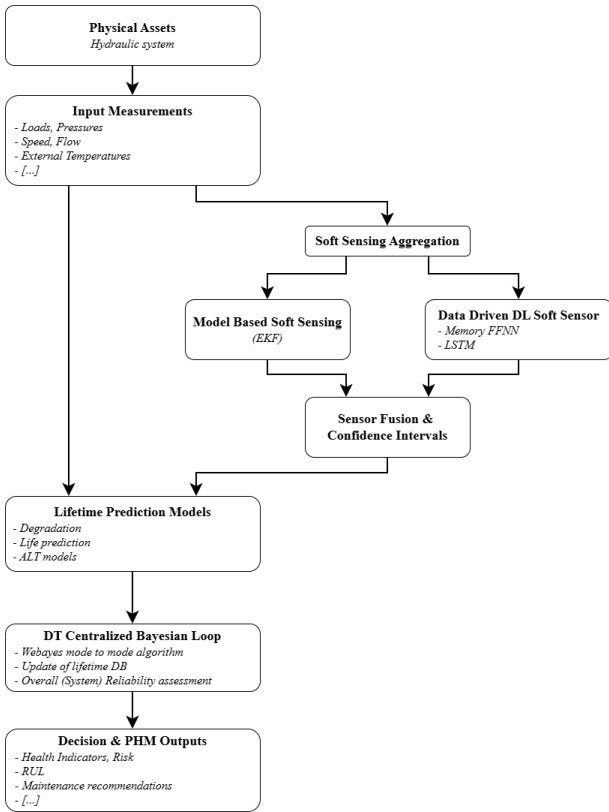


Figure 11. DT architecture with hybrid temperature soft sensing.

For cyclic thermal loading, fatigue-oriented models such as Manson–Coffin, coupled with Rainflow counting, can be deployed using the estimated temperature ranges.

The integration of ML and DL-based soft sensing thus extends the Digital Twin toward additional degradation modes. When time-to-failure databases are available, this framework allows recurrent “predict–measure–update” cycles using Weibayes formulations, with failure-mode-specific Weibull parameters, continuously updated as a function of temperature-induced degradation.

6. ANOMALY DETECTION AND DEGRADATION TRACKING

Some failure modes remain inherently difficult to capture using physics-based or cumulative formulations alone. These include abrupt phenomena and weakly cumulative mechanisms such as contamination or pollution of hydraulic circuits, cavitation onset, lubrication defects, or unexpected structural damage. To address these limitations, the proposed DT integrates vibration-based anomaly detection/degradation quantification using Self-Organizing Maps (SOM) coupled with the Mean Quantization Error (MQE).

The SOM operates as follow within the DT architecture: (i) SOM-MQE is deployed as a parallel and generic health indicator ; (ii) its activation and interpretation are explicitly conditioned on operating regimes, ensuring consistent comparisons under similar load and speed conditions ; (iii) it acts as a consistency and safety layer, providing early-warning capabilities and enabling a global override of model-based predictions whenever abnormal behavior are detected.

This positioning follows recent PHM works on vibration-based anomaly detection (see Lee and Park, 2024; and Radicioni, Bono, and Cinquemani 2025), while extending their use toward quantitative degradation variables, capable of architectural governance of the DT rather than standalone diagnostics.

6.1. Acceleration measurements and feature extractions

High-frequency acceleration measurements (above 5 kHz) constitute the entry point for anomaly detection on hydraulic components. Beyond the detection of localized structural damage, vibration analysis under cyclo-stationary operating conditions provides a robust baseline for long-term state-of-health comparison, particularly for rotating equipment operating in repetitive regimes.

Time series acquired from accelerometers are processed to extract a set of 29 features, ranging from simple statistical descriptors to more advanced spectral and time–frequency indicators, including FFT-based metrics, wavelet coefficients, and spectral kurtosis area calculations. These features form a high-dimensional representation of system behavior, illustrated in Fig. 16, and serve as inputs to the SOM-based monitoring layer.

6.2. Self-Organizing Map (SOM) algorithm with Mean Quantization Error (MQE)

SOM are unsupervised NN designed to project high-dimensional data onto a two-dimensional grid while preserving the topology of the original feature space (Kohonen, 2001). Similar operating conditions are mapped to neighboring neurons, forming a compact representation of nominal system behavior. In the proposed DT, the SOM is trained exclusively on healthy data, corresponding to pristine or near “good-as-new” conditions. Any significant deviation from this learned topology is quantified through the MQE,

defined as the average Euclidean distance between input vectors and their corresponding Best Matching Units (BMU). Each neuron is associated with a single bijective vector that has the same dimension as the input vector, called Codebook or weight vectors.

For a given dataset $X = \{x_1, x_2, \dots, x_N\}$ of N sample of data, the SOM matches each sample to its BMU :

$$QE_i = \|x_i - w_{BMU(i)}\|_{\text{euclidian}}$$

$$= \min_{p \in \text{neurons}} \sqrt{\sum_{k \in \text{dim } x_i} (x_{i, k} - w_{p, k})^2} \quad (28)$$

The MQE on the complete set of samples is equal to :

$$MQE = \frac{1}{N} \sum_{i=1}^N QE_i \quad (29)$$

With :

- x_i : the i th input data vector
- $w_{BMU(i)}$ is the weight vector of the BMU for data x_i

Healthy operating conditions are associated with low MQE values, while progressive degradation or abnormal events lead to increasing distances in the feature space, and sometimes the crossing of abnormal thresholds. The MQE therefore acts as a generic sensitivity indicator, capable of detecting both gradual drifts and abrupt changes, independently of the underlying physical degradation mechanism.

6.3. Process description

The SOM-MQE mechanism is trained and evaluated under distinct load regimes. In the present work, the operating space was discretized into five representative load conditions, each trained using healthy data, resulting in a single SOM with a 5×5 hexagonal topology. The training process is summarized in Fig. 12.

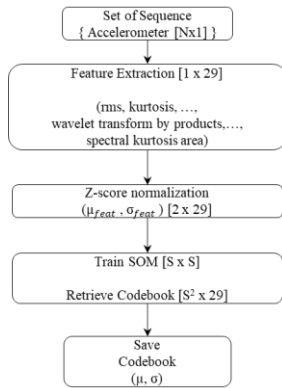


Figure 12. SOM Training process

During operation, MQE is computed continuously following the evaluation process shown in Fig. 13. Under highly contrasted operating regimes, multiple SOMs or load-specific activation strategies can be employed to preserve sensitivity and avoid false alarms due to regime changes.

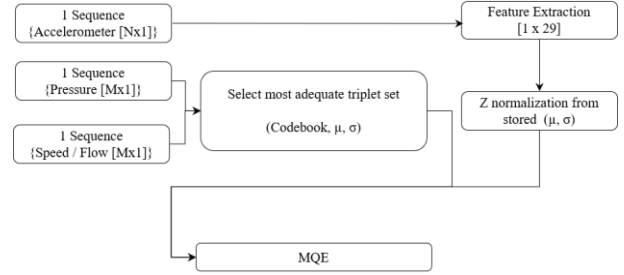


Figure 13. MQE Evaluation Process

6.4. Application to varying loads and incident detection

The SOM-MQE approach was deployed on a step-stress experiment with constant rotational speed and increasing load. Each MQE point corresponds to one minute of vibration recording at 19.2 kHz, evaluated on an hourly basis.

As illustrated in Fig. 14–16, MQE values increase noticeably at higher loads, revealing deviations from the original healthy topology. At each load plateau, transient increases in MQE are observed prior to stabilization, suggesting progressive wear-in effects and increased mechanical stress. Such behavior demonstrates the ability of SOM-MQE to capture early, non-modeled degradation trends.

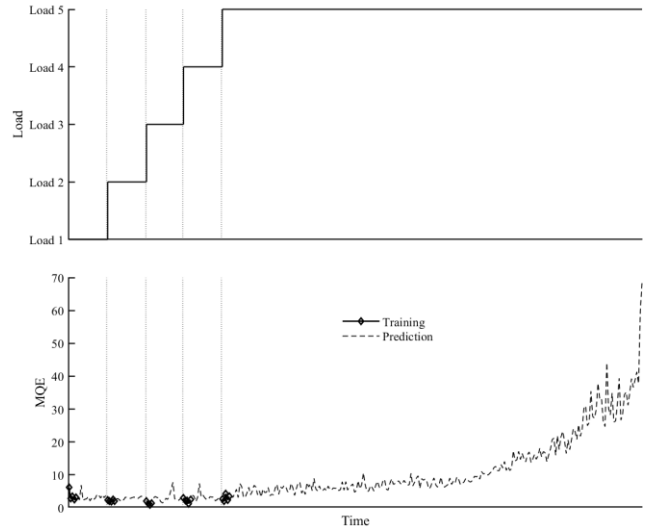


Figure 14. Evolution of the MQE according to the time & load

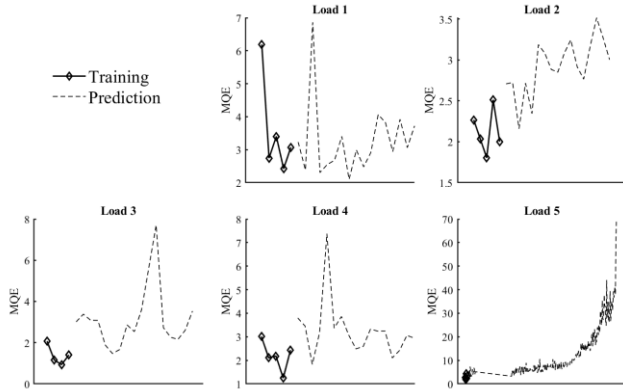


Figure 15. Detailed evolution of MQE

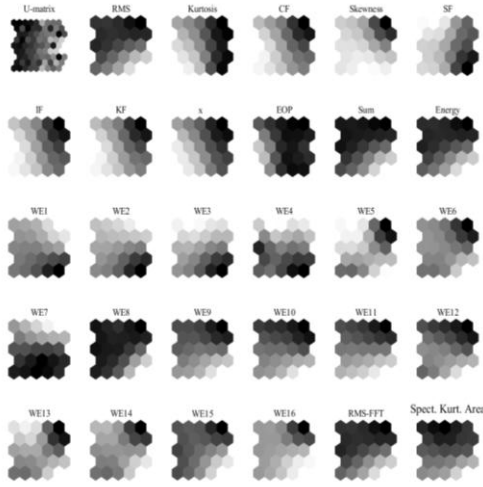


Figure 16. Sensitivity of SOM neurons according to the features.

6.5. SOM as a Supervisory Override Mechanism

As illustrated in Fig. 17, the SOM–MQE has a supervisory task, governing model validity within the Digital Twin. The MQE provides a continuous distance-to-nominal measure, which is mapped to a model applicability factor $\alpha(t) \in [0,1]$, for instance:

$$\alpha(t) = \exp\left(-\frac{\text{MQE}(t) - \mu_{\text{MQE}}}{\sigma_{\text{MQE}}}\right) \quad (30)$$

where μ_{MQE} and σ_{MQE} are estimated from healthy conditions under the same load regime. This factor directly governs the DT output by weighting nominal predictions and conservative bounds:

$$\text{RUL}_{\text{DT}}(t) = \alpha(t) \text{RUL}_{\text{model}}(t) + (1 - \alpha(t)) \text{RUL}_{\text{safe}} \quad (31)$$

With RUL_{safe} a conservative value to be selected with care.

From a Bayesian interpretation, the probability that the degradation model remains valid (given the observed behavior) can be developed at the system or multi-failure mode level, fostering a similar expression :

$$P(\text{Model valid} \mid \text{MQE}(t)) = \exp(-\beta \cdot \text{MQE}(t)) = P_{\text{valid}} \quad (32)$$

$$R(t) = P_{\text{valid}} \cdot R_{\text{model}}(t) + (1 - P_{\text{valid}}) \cdot R_{\text{degraded}}(t) \quad (33)$$

In addition, rapid variations of the MQE enable the detection of regime changes or incident-driven degradations (see Fig. 17), triggering an override of Digital Twin predictions and enforcing conservative decision-making when cumulative modeling assumptions no longer hold. This leaves room for further development of override decisional policies with techniques such as Reinforcement Learning.

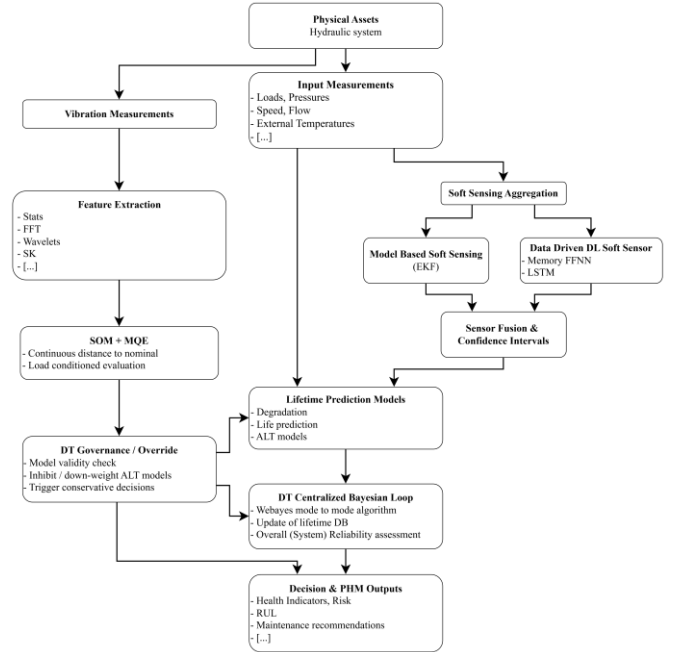


Figure 17. SOM supervisor

7. CONCLUSION

This work presents a reliability-centered Digital Twin architecture for PHM, combining mature techniques from reliability engineering, Bayesian estimation, and artificial intelligence into a coherent and deployable framework. The contribution lies in the fusion logic, uncertainty handling, and architectural governance.

The integration of SOM-based anomaly detection/degradation assessment as a generalized mean to override mechanism bridges a critical gap between cumulative modeling approaches and real industrial behavior, where incident-driven degradations frequently occur.

Future work includes the exploration of more expressive unsupervised architectures (e.g., autoencoders or temporal models), advanced information fusion frameworks for conflicting indicators, and the integration of uncertainty-aware decision algorithms. These extensions would further evolve the proposed DT from a diagnostic and

prognostic system toward an autonomous, reliability-driven decision support framework.

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