From Signals to Insights: Uncovering Latent Degradation with Deep Learning as a stepping stone towards Digital Twins of Failures (DTFs)

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***Abstract*— In the study, we investigate the application of deep learning using discretised hydraulic power signals for delineating healthy from non-healthy states on a hydraulic system of a rubber mixing machine. Using the concept of functional-productiveness, the study uses class labels determined as semi-supervised learning by relying on discretised signal behaviour and manually inputted target labels. The feature extraction process is performed through extensive data wrangling to extract discrete-domain features for training the neural networks. The study compares five deep neural network models, in which case the most suitable model is determined by the area under the receiver operator curve (AUC) and the time to train the network. The neural network architecture optimises via Genetic Algorithm (GA). The final result shows that GLobally convergent Resilient PROPagation with Smallest Absolute Gradient (GLPROP-SAG) outperforms other models regarding AUC and time to train the network.**

Keywords—industry 5.0, digital twins of failures, deep neural network, deep learning, energy-based maintenance, sustainable maintenance

I. Introduction

Rapid advancements towards Industry 5.0 (I5.0) following fundamental principles of sustainability, human-centricity and resilience [1] would not be achievable without technological support of Industry 4.0 (I4.0) features [2], such as Internet-of-Things (IoT) [3], Digital Twins (DT) [4], Circular Economy (CE) [5], Industrial Symbiosis (IS) [6], and many others. With high expectations in the way of social progress, many researchers engage in Sustainable Maintenance (SM) [7] and Energy-Based Maintenance (EBM) [8] to support and improve sustainable production. Although an existing body of knowledge primarily focuses on Predictive Maintenance (PdM) by incorporating waste-energy indicators, little effort has been made to understand and use primary energy indicators, such as hydraulic power.

Although an existing body of knowledge in the PdM domain uses Machine Learning (ML) and Deep Learning (DL) algorithms [9], some advocate that the actual advancements and altering of maintenance practice do not show the actual change of underlying constructs [10] that drive the evolution of industrial maintenance. The idea is to transition from time-domain to energy-domain parameters to improve maintenance decision-making (MDM) and conduct maintenance activities. Instead of using traditional CM (Condition Monitoring) practices that rely on waste energy (e.g., temperature, vibration), the idea is to transition towards primary energy indicators (Fig. 1). With the digitalisation of industrial assets; the idea is to switch from onsite to remote CM by using system parameters and DL algorithms. Namely, although the traditional maintenance practices rely on sensors used for CM that are mostly vibro-acoustics due to high frequency in the detection of anomalies, we perform an analysis using discretised hydraulic power signal (DHPS) as a hydraulic load profile within the system to detect potential leakages, wear and disturbances. For instance, by switching on to DHPS, we can gain insight into changes in power output, i.e., energy losses between the hydraulic pump and actuation device, which can suggest potential loss of power and suggest leakage (or wear). This also help us gain insight about the productivity loss or worse yet, product defects due to loss of actuation force or movement.

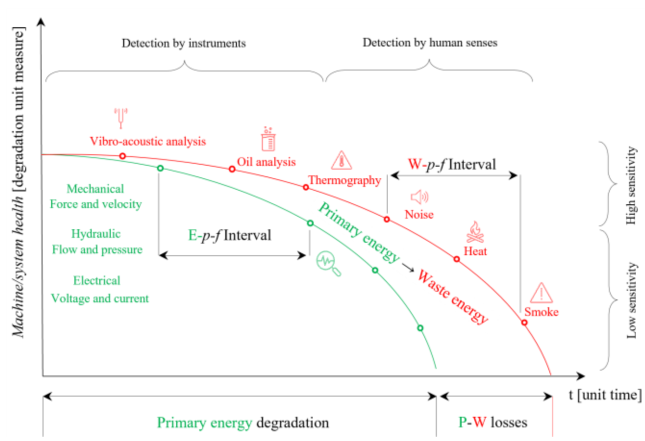

Fig. 1 Differentiation between the primary energy *p-f* curve (green line) and waste energy *p-f* curve (red line) [11]

Although the traditional notion of *productiveness* is understood as the number of units produced per time, we switch the focus to output quality by measuring the deviations in the actuation device (e.g., actuation speed). In addition, we also include the *functionality* notion as the component capacity to perform a specific action or a desired action. Hence, we merge the terms forming *functional-productiveness* for delineating degradational states that cause a reduction in either of the two concepts. For instance, a system can be fully functional but lacks productiveness. The system can also be productive (units produced per time), but those units may be flawed or contain defective products due to irregular movements and actuation force.

Therefore, the notion of functional-productiveness is introduced [12] for estimating the Quasi-fault (QF) events, where the idea is expressed as binary [0, 1] if it breaks the imposed Functional-Productiveness (FP) threshold. The notion of FP is used to set thresholds for delineating "Healthy" from a "Non-healthy" state, depicted as "*None*" and "*Quasi-Fault*" labels, respectively. Such process monitoring practice enables tracking disturbances (e.g., loss of productivity/functionality) and suggests maintenance activities. Such an approach allows signals to be used: (i) for diagnostic and prognostic purposes by comparing deviations; (ii) for decision-making purposes by observing target (loss) function; (iii) for system (re)design (production line) purposes – the amount of system power required to make a unit of product; (iv) for optimisation purposes because energy can be transferred easily into monetary value; and (5) for sustainable purposes as energy-efficient and environmental-friendly adjustments of the process.

The DHPS signal is used for delineating *Healthy* from *QF* states of the hydraulic control system. We rely on a deep neural network with different propagation algorithms and the use of GA (Genetic Algorithm) [13] to optimise the network architecture. The rest of the study includes the following. In the second section, we explain the experimental design, data wrangling and data analysis used for designing a neural network. The third section represents the results obtained from the study. The fourth section describes the discussion, including implications and limitations of the work. The last chapter describes study conclusions and future research directions.

II. METHODOLOGY

A. Hydraulic System of a Rubber Mixing Machine

The hydraulic system of a rubber mixing machine (RMM) that controls the saddle movement depicted in Fig. 2 comprises of: (1) tank; (2) axial piston pump with (3) regulation valve for displacement; (4) manifold block; and (5) actuators – linear closing chamber door and rack-and-pinion for controlling the saddle movement of the opening. The data acquisition includes non-destructive instruments: (6) HYDAC AS3000; (7) HYDAC CS1000; (8) turbine flow meter; (9) HYDROTECHNIK MultiHandy 2045 reading of power, flow and pressure; (10) communication module; (11) PC for data acqusition; and (12) SCADA (Supervisory Control And Data Acquisition) system for measuring cylinder speed, saddle position, temperature, proportional valve activation (time), filter contamination level, tank oil level, and energy consumption by individual processes. In addition, (4) destructive measurements via oil sampling for laboratory analysis are performed regarding physio-chemical properties of hydraulic fluid (i.e., viscosity, density, and total acid number), including elemental analysis of the fluid in search for the presence of wear via Wavelength Dispersive X-ray Fluorescence spectrophotometer.

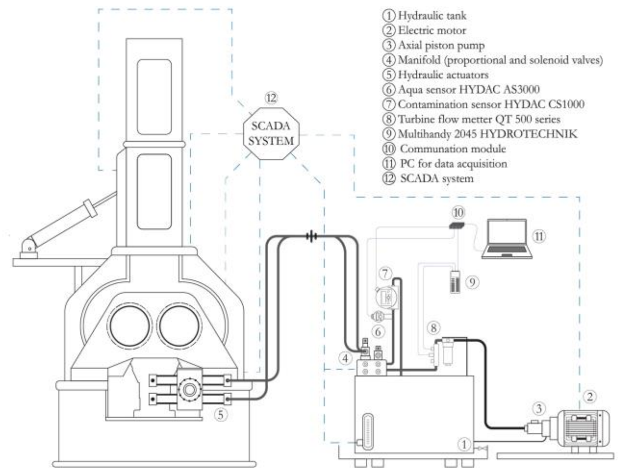

Fig. 2. RMM process with data acquisition instruments [10]

Finally, qualitative data (5) concerning class labels C_y, $y \in \mathbb{R}$, $\mathbb{R} = \{1, 2 \ldots n\}$ is used for labelling. The operator labelled faulty conditions in case of disturbances and those that are not faulty that can be used later in penalising conditions. Labels for classifications used are *None* and *QF* conditions.

B. Data wrangling

Data acquisition is performed 24/7 since the RMM production works non-stop in three shifts of 8 hours. The labelling of the data is performed on selected 20 hydraulic cycles daily. *Data wrangling* includes data (pre)processing in the following steps: (1) *data discretisation* is firstly performed on a hydraulic signal to generate time-discrete domain features by transferring continuous-time signals to discrete-time domain $x(t) \rightarrow x[n]$, such that $x(t) \rightarrow x[nT]$ with f_s = 10 Hz; (2) *data integrity* is performed to assure validity and reliability of data (e.g., storage, file type, quality); (3) *data filtering* is performed to reduce noise and redundant data; (4) *data scaling* is performed by *z*-standardisation; and finally (5) *data split* is performed to divide data into training (60%), testing (20%) and validation (20%).

C. Deep neural network training and topology optimisation

Traditional Multi-layer perceptron is considered a Feed-forward Artificial Neural Network. The *training algorithms* used for the comparison of results include BP-ANN (Backpropagation) and RPROPs (Resilient back propagations) learning algorithms [15]. The weights and biases have implied a learning rate that changes when the gradient does not change sign. The RPROPs variants [16] used include RPROP with resilient backtracing (RPROP+), without backtracing (RPROP-), GLPROP-SAG (Globally convergent resilient propagation with smallest absolute gradient), and GLPROP-SLR (Globally convergent resilient propagation with smallest learning rate) algorithms for training [17].

The parameters set for training the networks are given as follows. The stopping criteria (threshold) for partial derivates is set to *1* with maximum training repetitions of 10^5. The *Z* score standardisation is used for scaling the data. The activation function is chosen as the logistic-sigmoid function. For excluding random processes and for repetition of the results, the seed is set as *123*.

For the optimisation of the architecture and hyperparamters of DNN (Deep Neural Network), we used GA [18]. The default hyper-parameter setting for the learning rate used in *Keras* is *0.001*; however, the *0.05* value for reducing the learning epochs is set instead. The population size is set to *20* and generations to *10*. The parent selection node is the *roulette wheel*, and a *uniform crossover* method is defined. The random reset mutation is set with a *10%* probability, and the survival method is fitness-based with an elitism of *10%*. The PC training network is Intel® Core TM i3-4170 3.7 GHz, 8 GB RAM, GeForce GT1030, and 64-bit OS.

III. Results

A. Raw data extraction results

Based on the acquired data, examples of hydraulic power signals were studied. The changes between the beginning (Fig. 3 at 12-10-2021) and after 21 days (Fig. 3 at 31-10-2021) showed an increased power change in signal deviations. Also, deviations were observed on 09-11-2021, where the idle position was not observed in the signal, and significant changes in anomalies started emerging. Finally, significant abnormalities can be seen in the last signal (Fig. 4 on 04-12-2021). The sample of 980 signals is used for discretisation and training/validation of the DNNs.

The movement speed of the actuator: for fast (*T1*) and slow (*T2*) opening; idle (*T3*) position; and fast (*T4*) and slow (*T5*) closing with rack-and-pinion cylinder shows significant variations in the signal movement (Fig. 4). There was no significant variations (>50°C) and water saturation for having a high impact on physio-chemical properties of the fluid (Fig. 5). The contamination level of the fluid was somewhat moderate to high according to ISO 4406:17 (Fig. 6): $\mu_{\geq 4}$ = 20.81±0.04, $\mu_{\geq 6}$ = 20.48±0.05 and $\mu_{\geq 14}$ = 16.91±0.04. However, given that elemental analysis showed no elemental particles ≥10 ppm (e.g., Copper, Iron, Chromium), except for Si (Silicon) particles >20 ppm, it is safe to presume that rise of Si is due to dirty environment that contaminated the oil. However, since the maintenance activities were conducted regularly, which included regular filter replacement process [19], oil refilling and replacement, the same process may cause bias in the estimation of the results given that hydraulic power significantly changed in comparison to the start of the experiment.

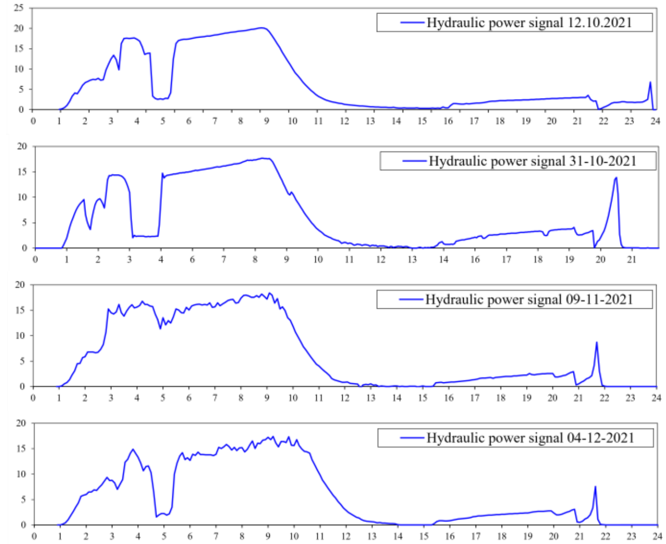

Fig. 3. Hydraulic power signal (*y*-axis) and time [sec] (*x*-axis) per cycle

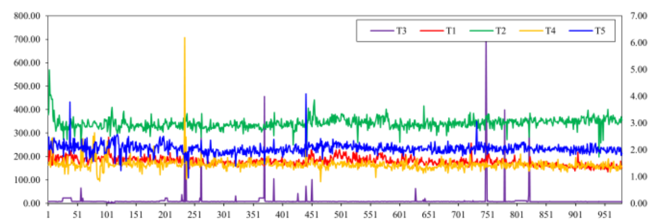

Fig. 4. Actuator speed readings for idle *T3* (y_1-axis) and opening *T1-T2* saddle and closing *T4-T5* saddle time (y_2-axis) concerning cycles (*x*-axis)

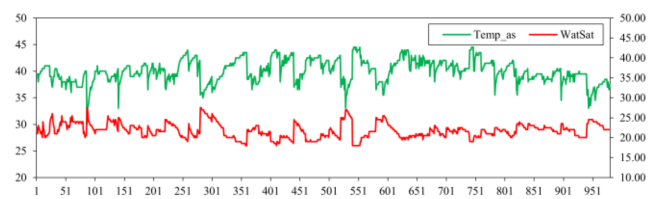

Fig. 5. Aqua sensor signal readings for temperature (y_1-axis) and water saturation (y_2-axis) concerning cycles (*x*-axis)

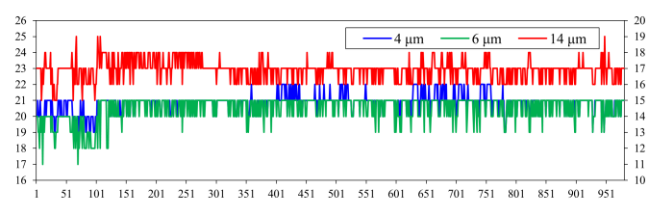

Fig. 6. Contamination sensor readings based on the ISO4406:17 for particles ≥4 µm and ≥6 µm (y_1-axis) and ≥14 µm (y_2-axis)

B. Discretised hydraulic power signal features

We divide the signal with opening, idle and closing saddle regimes based on the proposed discretisation. Each signal part is used as discretised value as features given in TABLE I. These features are then used from 980 samples for every regime to delineate healthy from non-healthy conditions.

TABLE I. Discrete-domain features

Feature	Formula
Mean value	$Mean = \frac{1}{n}\sum_{i=1}^{n} x_i$
Standard deviation	$StDev = \sqrt{\frac{\sum_i^n x_i - \bar{x}}{n-1}}$
Root Mean Square	$RMS = \sqrt{\frac{1}{n}\sum_i^n {x_i}^2}$
Minimum	$Min = \min\,(x_i)$
Maximum	$Max = \max\,(x_i)$
Interquartile range	$IQR = x_{3Q} - x_{1Q}$
Quartiles (Q1; Q3)	$nQ_{1;3} = x_{(k)} + a(x_{k+1} - x_k)$
Peak-to-peak	$P_P = \max(x_i) - \min\,(x_i)$
Skewness	$Skew = \frac{\sum_i^n (x_i - \bar{x})^3}{(n-1)\cdot\sigma^3}$
Kurtosis	$Skew = \frac{\sqrt{n(n-1)}}{(n-2)} \cdot \frac{\sum_i^n (x_i - \bar{x})^3}{(n-1)\cdot\sigma^3}$

The investigation of the LCM's analysis did not indicate significant insights from the system due to the constant trend of water saturation and particle contaminants, suggesting the absence of wear, the DHPS and actuator movements provided different insights.

C. *Deep neural network architecture*

The initial model consisted of four hidden layers (*H1-H2* 6 nodes; *H3* 5 nodes and *H4* 2 nodes). After tuning hyperparameters and topology of the network(s) using GA, we reduced it to *H1* (7 nodes) and *H2* (6 nodes) (Fig. 7).

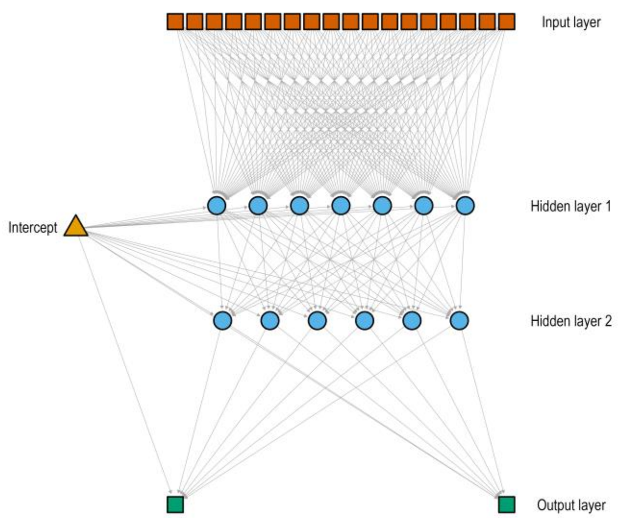

Fig. 7. Sigmoid activation function; algorithms have 10^5 repetitions (training) and threshold for partial derivatives of the error function as stopping criteria that are set to 1; optimisation algorithm for population (n=20) with ten generations; Parent selection = Roulette wheel; crossover method = uniform; mutations = reset with probability 10%; survival method fitness-based with elitism 10%.

D. *Classification results*

Data used for classification shows that a higher percentage of data contains healthy (52.7%), i.e., "None" faulty data (TABLE II.). Given the imbalanced sample, it is usually recommended to use Area under Receiver Operating Curve (AUC) metric for measuring the classification accuracy, which is done in this case. However, we also included classification accuracy results, in which case the evidence suggests that traditional BP-DNN performed better than other models. In addition, although BP-DNN performed better than other models (TABLE III.), the cost of training the network showed that it took almost six times more time than other models (TABLE IV.). Moreover, the results showed that given the AUC metric, the GLPROP-SAG, BP-DNN and RPROP+ showed the highest AUC score; however, in terms of training the network and overall results, the GLPROP-SAG seems to outperform other models.

TABLE II. DATASET PROPORTION USED IN TRAINING DNN

	Dataset	Training	Testing	Validation
None	0.527	0.522	0.561	0.515
QF	0.473	0.478	0.439	0.485

TABLE III. CLASSIFICATION ACCURACY

	None	QF	Test	Valid.
BP-DNN	0.985	0.985	0.985	0.981
RPROP+	0.964	0.964	0.964	0.968
RPROP-	0.944	0.944	0.944	0.930
GLPROP-SLR	0.944	0.944	0.944	0.936
GLPROP-SAG	0.964	0.964	0.964	0.955

TABLE IV. AREA UNDER ROC RESULTS OF MODELS

	AUC-None	AUC-QF	Overall	Time
BP-DNN	0.944	0.950	0.947	185.9s
RPROP+	0.950	0.939	0.945	50.31s
RPROP-	0.940	0.940	0.940	34.73s
GLPROP-SLR	0.940	0.933	0.937	31.14s
GLPROP-SAG	0.940	0.953	0.947	33.99s

IV. DISCUSSION

From the obtained analysis, the results suggest the following. By focusing on the FP concept for labelling classes with potential disturbances as *QF*, the use of DNN helped delineate healthy from non-healthy conditions with high accuracy (>95%) using discretised hydraulic power signal. A novelty in comparison to traditional CM practices is that the study uses primary hydraulic power (i.e., hydraulic load profile) instead of waste power (i.e., temperature, vibrations) signal for machine diagnostics.

Also, the traditional approach of using LCM practice was inconclusive since there have been no observed variations in terms of contamination that could lead to a potential indication of wear. This, however, can be attributed to the ongoing practice where operators perform routine filter replacements, oil replacements and, in some cases, oil refilling, which causes bias in estimating potential degradation in physio-chemical properties of the oil.

Regarding data analysis and validation, in terms of classifying labels, out of five neural network models, traditional BP-DNN is shown to outperform other models. However, diving deeper into the analysis, the model took more than 3 minutes to train, just for the sample of 980 records, which proved to be six times higher than other models. In addition, since there has been a slight imbalance of obtained classes, the AUC metric is used to check for the overall classification of models, in which case the GLPROP-SAG model showed to have the same overall AUC score as BP-DNN but outperformed the BP while training the network and proved to be the more compelling result.

The study's limitations can be related to the imbalanced dataset, which affects the model's performance. Secondly, the presence of bias due to (ir)regular maintenance activities and lack of maintenance log files can cause problems in determining the root causes of faulty states. Finally, the current study only relies on the hydraulic control system example, limiting the generalisation of results to other energy domains, although the concept remains the same.

V. Conclusion

The study uses a novel approach in CM practice by relying on discretised hydraulic power signals instead of traditional vibroacoustic or temperature signals. The proposed functional-productiveness notion for delineating the healthy from the non-healthy state, such that disturbances can be addressed while the system is operational, proved acceptable and more compelling than using total failure events for classification. The results obtained from models show that globally convergent resilient propagation with the smallest absolute gradient and optimisation of network architecture using GA outperforms other models by the measure of AUC and time to train the network. The following studies will use extensive data from generated log files, destructive measurements via microscopic evaluation of component surfaces and topology for associating degradation with potential wear of hydraulic components. The proposed idea is the first stepping stone in what we believe that the future of industrial maintenance will be dedicated to creating Digital Twins of Failures (DTFs).

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