Maintenance Practice Performance Assessment of Hydraulic Machinery: West Balkan Meta-Statistics and Energy-Based Maintenance Paradigm

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***Abstract*— As a consequence of accepting sustainable initiatives, e.g. Green Deal, sustainable maintenance attracted significant attention in academia. However, observation of low market intelligence and lack of sustainable goal-oriented philosophy has been reported. The article proposes the Energy-Based Maintenance (EBM) paradigm to fulfil the needs of sustainable manufacturing philosophy. The EBM implicitly consists of two concepts: Functional-Productiveness (FPC) and Comparative Functional Productiveness (CFD). Namely, the core of FPC is to propose a new view in understanding the nature of functionality by delineating static (maintenance) events (e.g., total failure, death, etc.) from dynamic (process) events (e.g., quasi-faults, leakage, contamination, etc.). The CFD uses FPC and dynamic (process) events and acts as a catalyst in reducing noise for feature extraction by comparing system behaviour (cylinder response) and energy consumption. Demonstration on a case study of proposed EBM practice versus traditional ones is done on three bulldozers CAT D8R. The results show reduced oil waste and energy consumption and improved MTBF; however, the stoppages are censored due to constant monitoring and inspection.**

Keywords—energy-based maintenance, hydraulic systems, functional-productiveness concept, comparative functional dynamics, machine learning

I. INTRODUCTION

A. *Traditional Maintenance Practices – pre-IoT era*

Academicians occupied with industrial maintenance have long sought to explain how maintenance should be perceived and employed practically in an industrial environment. To frame it, the BSI (British Standards Institution) published a standard which defines maintenance as: "…*the combination of all technical and administrative actions, intended to retain an item in or restore it to, a state in which it can perform its desired function*" [1]. The BSI definition of maintenance implicates two basic maintenance strategies that most researchers oblige with: Corrective Maintenance (CM) and Preventive Maintenance (PM) [2]–[5]. The CM also belongs to run-to-failure and reactive maintenance practice, while PM consists of Time-Based Maintenance (TBM) and Condition-Based Maintenance (CBM). Unlike the CM approach, where the goal is to reduce the severity of the failure, the PM dedicates to finding and preventing, or in other instances, reducing the frequency of failures. The CM approach dealt with supplying standby machines, stocks of spare parts, and providing labour training for repair, which, in turn, consumed a significant portion of time and money. At the time, these alternatives soon fall short of expectations, making PM more compelling. However, although TBM provided opportunities to improve operational effectiveness eventually had a hard time fulfilling the needs of more complex and sophisticated systems. Leveraging stoppage' expenses while preventing failures, maintenance optimisation became an extensively popular topic [6], [7].

The maintenance optimisation era forced peers to shift more attention to optimal strategies, aiming to reduce unnecessary activities, thus, creating a solution space for the CBM approach. Acceptance of the CBM paradigm experienced unprecedented interest in academia [7], [8], mostly due to disruptive technologies. Some argue that CBM was introduced in 1975 [9], while others state that it dates back to the late 1940s when Rio Grande Railway Steel Company introduced the concept, later adopted by the US Army [10]. The uniqueness of CBM became apparent in its distinctive way of reducing unnecessary activities by taking action only in the case of abnormality. The topic became extensively interesting in practice and academia, although lacking proper characterisation. Eventually, Jardine et al. [11] took the credit by stating that CBM: "*…is a maintenance program that recommends maintenance actions based on the information collected through condition monitoring.*" Although elusive, one can conclude that, unlike TBM, actions are taken when acquired data shows abnormal behaviour. Jardine et al. argue that, for CBM to be functional, two data types are required: event data (e.g., repair or preventive actions) and monitoring data (e.g., temperature and pressure). What is interesting is that the CBM is considered the same as PdM by various authors [3], [9], [10], [12]. The author of this article argues that this could be a misconception and misinterpretation of these practices. The first reason is that different underlying concepts drive the methodologies to different goal-oriented objectives. The second reason is that both policies utilise other available maintenance practices and technology.

B. *Maintenance Practices – post IoT era*

The first aspect of CBM, the diagnostic aspect [13]–[15], Fault Detection and Isolation (FDI) [16], [17] or RCA (Root Cause Analysis) [18], deals with fault detection, isolation, and identification when the failure occurs. On the other side, prognostics deals with fault anticipation, i.e., providing decision support before the failure occurs. These two aspects frame the CBM program [2], [3], [11], [19], in addition to data acquisition, data processing, and decision-making, which are three essential steps of CBM.

Neo-Jardinians, who champion the CBM program over other maintenance concepts, mostly focus on the prognostics aspect [20]–[25], especially the Remaining Useful Life

(RUL) prediction. The prognostic aspect evaluates the historical diagnosis results and anticipates RUL of safe operation, relying mostly on statistical approaches [10]. Conversely, PdM practice mostly utilises the real-time data-driven approach by monitoring signal deviations from disturbances affecting specific machining processes, including diagnosis and prognosis.

We propose that CBM is not identical to PdM to present the claims further. To some extent, similarities exist, and PdM somewhat implies CBM (diagnosis and prognosis); however, it does not address the same processing information. Namely, the CBM policy belongs to preventive and predictive maintenance practice. Hence, if data analysis relies on maintenance (failure) data, it belongs to CBM practice. If the data analysis relies on control (process) data, it belongs to PdM. For CBM, the goal is to prevent stoppages (failures), while for PdM, the goal is to use feature extraction methods to understand and act upon anomalies or quasi-failures that can cause degradation and eventually stoppage.

With that in mind, the CBM's maintenance activities rely mostly on failure data with statistical or analytical modelling to predict and perform needed actions. For instance, Cox's Proportional Hazard Modeling usage in CBM emphasises high dependence on failure data for diagnosis [2], [26]. Conversely, PdM relies more on process control data (e.g., vibration, noise, temperature) to predict the impact or reduction of operational performances. In this particular realm of maintenance (PdM), PCA (Principal Component Analysis) gained prominence after the 2000s [27], [28] for determining the replacement control limits. More recently, the method of PCA has been applied in manufacturing [29], the aerospace industry [30], and infrastructure [31], also extended with an unsupervised machine learning approach [32]. The development of sensor technology, remote monitoring (e-maintenance[33]), and typologies suggested by Veldman et al. [3], inspired the author to propose this maintenance juxtaposition.

Likewise, numerous programs exist within the literature on the lower level of decision-making; for instance, PHM (Prognostics and Health Management) [34] program extends the traditional CBM's diagnostic and prognostic aspects with LCM (Life Cycle Management) capabilities. Some authors consider PHM a synonym for CBM [17], [35], although without proper terminological explanation to support such claims. Similarly, the SHM (Structural Health Monitoring) program closely reflects CBM, although only the condition-monitoring part of CBM focuses on structural damage detection. The SHM has been widely applied in aerospace [36], civil [37]–[39], and mechanical engineering structures [40]. Unlike many programs at the tactical level that CBM consists of, the SHM [41], however, mostly relies only on vibration or noise data for pattern recognition [42], with more details in the diagnostic aspect [43]. Putting all together, one can conclude that PHM and SHM closely relate to each other, with differences in analysis detail. These programs should be encompassed within the PdM practice, emphasising high dependency on real-time signal processing and decision-making based on control (process) data.

C. *Energy-Based Maintenance (EBM) Paradigm*

More researchers have recently advocated the need for sustainable maintenance practices [44]–[46]. From the current energy-oriented research [47], [48] evidence suggests that most of the research includes data-driven statistical and mathematical modelling for decision-making purposes [49]. Unlike previous maintenance practices where the goal is profit-driven, the EBM adds a dimension of sustainability [50]. Besides, the EBM paradigm's prominent research is monitoring energy as a performance parameter. As previous research only includes energy as a sub-dimension of financial effectiveness and efficiency of maintenance activities for optimisation purposes, with the help of available ML (Machine Learning) and DL (Deep learning) techniques, the energy consumption profiles (ECP) [51], [52] associates with the system health.

Moreover, by monitoring ECP, one can conclude the degradation process of a particular machine or component. Indeed, the logical pattern is that the actuator element's degradation performance (e.g., cylinder, motor) is strongly associated with the components' energy degradation processes, considering that energy follows a logical serial relationship. For instance, a hydraulic system of serial components transforms the energy from electric input to mechanical work through hydraulic (fluid) energy. Thus, the degradation of components within the system through, for instance, contamination [53] produces oil degradation, viscosity change and leakage – resulting in volumetric, thus energy losses. From such a logical presupposition, the benefit is that by monitoring energy losses between components' power ports, i.e., input and output, one can easily follow a particular component's degradation state. Interestingly, unlike traditional maintenance practices, the EBM practice consists of threefold information from monitoring just a simple parameter as ECP. For instance, by monitoring ECP, the resulting information includes:

- energy consumption as monetary value = financial;
- energy degradation = fault and failure assessment;
- energy waste = environmental responsibility.

Thus, measuring and monitoring energy can indicate the potential wear within the system and suggest conducting maintenance activities. However, it can also reflect the environmental consequence and financial losses associated with the failure since it can be transferred into monetary value. As a result, data can provide much more insight into the system's health, trigger maintenance actions, or provide financial and sustainability effectiveness information.

D. *Research Rationale and Aim of the Study*

This research aims to provide meta-data on hydraulic industrial and mobile machinery to compare future studies interested in implementing sustainability or energy-oriented maintenance policies. The first goal is to deliver various maintenance practice characteristics and outcomes within West Balkan countries. Secondly, the aim is to reflect the lack of underlying concepts and goal-oriented philosophies behind each maintenance practice compared to EBM. Thirdly, the idea of functional productiveness for clear apprehension and improving the benefits of monitoring ECP is provided. Finally, the conceptualisation of the system's working behaviour, i.e., dynamics, must distinguish the functional-productive from the non-functional-productive system as Comparative Functional Dynamics (CFD) is given.

The rest of the study is explained in the following. The methodology section provides a questionnaire-based formulation narrative for the extraction of empirical data. The third section proposes and explains the concept of FPC through formulas and illustrations. The following section explains the concept of CFD and its possible application. The fifth section provides the meta-data of maintenance practices within West Balkan countries. Finally, the last section discusses the benefits and setbacks of EBM over other maintenance practices and sets concluding remarks, implications and contributions to the literature.

II. Methodology

A. *Research Methods*

The survey design was done in the previous study (see [54]) since no standardised survey instrument is used to extract all maintenance features and associated activities. Within the EBM paradigm, the FPC is given to estimate the system's functional and operational state. In addition to the FPC, the CFD apparatus serves as a comparison tool for the energy consumption mode and estimates deviation that reinforces the FPC by penalising outliers that do not show degradational performances. Finally, the author discusses the advancements of FPC and CFD and the philosophy behind the concepts as EBM pillars and compares the EBM with other maintenance practices.

B. Survey Design and Application

The questionnaire-based survey is set for the region of West Balkan territory. The survey is disseminated to companies that utilise hydraulic mobile and industrial machines for servicing and manufacturing purposes. The questionnaire instrument validation is developed through three stages: (1) survey design – literature review, detecting features, and drafting the survey (2) survey simulation with validity and reliability testing; (3) survey analysis – meta-data, data sorting and filtering in respect to eligibility criteria, and evaluation of empirical evidence collected. Data collection includes empirical evidence from companies' databases from at least 10000 working hours (e.g., at most previous three years assuming at least two working shifts). Raw data from the survey is aimed at companies utilising different maintenance practices. Differentiation is made between maintenance practice and maintenance policy. Namely, most companies do not have generally written or accepted policies (e.g., CBM). However, they practice CBM through condition monitoring by utilising expensive high sensors and reacting abnormally.

Indeed, many companies apply various practices to their equipment after filtering data. Some may also have both CM and PM practice in a case of new equipment where enough data is unavailable; however, after unique evaluation, practices are determined based on the philosophy behind the applied practice. The survey consists of meta-data (e.g., age, pressure, flow), maintenance activities (e.g., filter management, oil monitoring), tools (e.g., monitoring sensors, data analysis tools), and maintenance practice outcomes (e.g., MTBF, hydraulic oil waste, energy waste).

C. *A Case Study in Open-pit Coal Mining*

The monitoring procedure includes systematically acquiring data from mobile machines from January-December 2020. Some of the most important data for comparative analysis are given in Table I. The fuel consumption per year (FCY) is transformed as one litre-diesel into 10 kWh later for analysis. Maintenance activities are performed according to the energy goal-oriented philosophy supported by the EBM paradigm.

TABLE I. Meta Data of Three Bulldozers

	Hydraulic machinery meta-data[a]				
	MH	***MA***	***FCY***	***HFW***	***TBF***
CAT D8R	4405.6	6	116183	0.021	2471*
CAT D8R	3354.5	3	96534	0.017	1927*
CAT D8R	3915.0	3	113681	0.015	3211*

a. *MH – Machine working hours during 2020; MA – Machine Age [years]; FCY – Fuel Consumed per year [lit./y]; HFW - Hydraulic Fluid Wasted [lit/hour]*
**Data includes censoring with stated random failure.*

The monitoring procedure is subjected to operational personnel who perform work with a bulldozer and monitor pressure and flow deviations, with the latter being more important to detect leakages. However, the concepts of CFD and FPC are only partially implemented for several reasons: too much data per day for acquisition, insufficient personnel to perform data acquisition, and a harsh working environment. Therefore, applying CFD and FPC is done at the end of each work shift to detect potential anomalies (e.g., wear, leakages).

III. Functional-productiveness Concept

Defining failure as "…*termination of the ability of a system to perform a required function"* [1] can be considered a formulaic statement since it lacks quantitative determination of ability and functionality, which is where it is assumed the problem resides. To address it, *functional-productiveness* is used instead of functionality to determine the working process as true quantitatively (1) or false (0). The ability is replaced with the term *capability* as "…*system or unit capacity to transfer power*" with ability values as true (1) or false (0). If we consider that power (P) is a rate (t) at which work (W) is done, then defining functional-productiveness must be done both for work and time.

Reasonably, if we define functional-productiveness of both time (x-axis) and work (y-axis), failure is a two-dimensional space of a function. It, therefore, must oblige both work control limits and time-space control limits (fig. 1). Nevertheless, let us communicate the argument by stating that quasi-failure of a system is "*the inability of a system to be functionally-productive, where the functional-productiveness* (ψ) *is the quantitative capability of work* (W_ψ) *and time* (T_ψ) *required to create a product or provide a service*". Therefore, we are quantifying functional-productiveness as:

$$\psi_i = \begin{cases} \psi_{W_i} = 0 \text{ if } \mathrm{BCL}(W_\psi)_i > W_{\psi_i} \vee W_{\psi_i} > \mathrm{UCL}(W_\psi)_i, else\ \psi_{W_i} = 1 \\ \psi_{T_i} = 0 \text{ if } T_i > \mathrm{UCL}(T)_i, else\ \psi_{T_i} = 1 \end{cases}, \quad (1)$$

$W_{\psi i}$ work required to be performed, T period in unit time for acting, UCL and BCL with index values $i=1,2,3,\ldots n$ are upper- and bottom-control limits due to change over time (assuming natural degradation, e.g., wear process) (fig. 2). Hence, considering that power is time derivative of work; thus power (P_ψ) function depends on the system dynamics and imposed requirements by the actuation device:

$$\psi_{P_i} = f\big(W_i(F), T_i(q)\big) \quad (2)$$

one can conclude that functionality is a two-dimensional space process. In that sense, the functionality of a system is dependent on work. Since work is done by compressing the fluid in the hydraulic system, functional-productiveness is a derivative of pressure and volumetric flow.

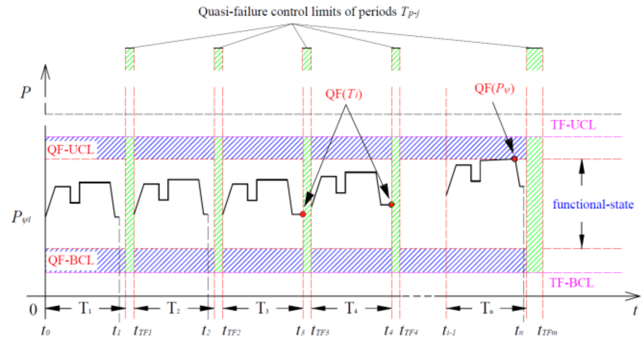

Fig. 1. Functional dynamics concept of demanded power by the system and a given period considering traditional static control limits (*legend*: TF-UCL = total failure upper control limit; TF-BCL = total failure bottom control limit; QF-UCL = quasi-failure upper control limit; QF-BCL = quasi-failure bottom control limit; t_{pi} = time to create a product)

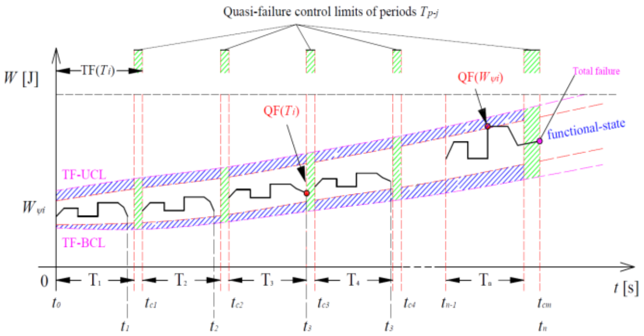

Fig. 2. Functional dynamics concept of demanded work by the system and a given time window considering dynamic control limits (legend: TF-UCL = total failure upper control limit; TF-BCL = total failure bottom control limit; QF-UCL = quasi-failure upper control limit; QF-BCL = quasi-failure bottom control limit; tpi = time to create a product)

To set the periods T_p, we can use Moving Average (MA) and determine and interpolate potential cycle-times (t_{p-j}) based on the real-time available values of t_i as:

$$t_p = \frac{1}{n}\sum_{j=1}^{k} t_{p-j} \tag{3}$$

hence, interpolating boundaries for functional-productiveness of T_p is done by setting quasi-failure control limit QF(T_p) and total failure control limit TF(T_p) of j periods as:

$$QF(T_p) = \frac{1}{n}\sum_{j=1}^{k} t_{p-j} \pm 2 \cdot \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(t_{p-j} - \mu_{t_{p-j}}\right)^2} \tag{4}$$

$$TF(T_p) = \max(t_{p-j}) + \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(t_{p-j} - \mu_{t_{p-j}}\right)^2} \tag{5}$$

Max t_j is the maximum value of machine cycle times t_j before period p, and $TF(T_p)$ is calculated by the sum of a sample's max cycle time and standard deviation before period T_p. μ_{tj} represents the mean values of machine cycle times before period p.

$$\psi_{T_{p_i}} = \begin{cases} \psi_{T_{p_i}} = 1 \; if \; T_{\psi_{p_i}} < QF\left(T_{\psi_{p_i}}\right)_{UCL} < TF\left(T_{\psi_{p_i}}\right)_{UCL} \\ else \; \psi_{T_{p_i}} = 0 \end{cases} \tag{6}$$

The same method we used to interpolate the value of $W_{\psi p}$ as:

$$W_{\psi_p} = \frac{1}{n}\sum_{j=1}^{k} W_{\psi_{p-j}} \tag{7}$$

hence, interpolating functional-productiveness of work $W_{\psi p}$ and setting quasi-failure control limits using j periods:

$$\psi_{W_{p_i}} = \begin{cases} \psi_{W_{p_i}} = 1 \; if \; W_{\psi_{p_i}} < QF\left(W_{\psi_{p_i}}\right)_{UCL} < TF\left(W_{\psi_{p_i}}\right)_{UCL} \wedge \\ TF\left(W_{\psi_{p_i}}\right)_{BCL} > QF\left(W_{\psi_{p_i}}\right)_{BCL} > W_{\psi_{p_i}}, else \; \psi_{W_{p_i}} = 0 \end{cases} \tag{8}$$

where quasi-failure upper boundaries for work $W_{\psi pi}$ are set as:

$$QF\left(W_{\psi_{p_i}}\right)_{UCL} = \frac{1}{n}\sum_{j=1}^{k} W_{\psi_{p-j}} + 2 \cdot \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(t_{p-j} - \mu_{t_{p-j}}\right)^2} \tag{9}$$

$$TF\left(W_{\psi_{p_i}}\right)_{UCL} = \max\left(W_{\psi_{p-j}}\right) + \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(W_{\psi_{p-j}} - \mu_{W_{\psi_{p-j}}}\right)^2} \tag{10}$$

and quasi-failure bottom boundaries for work $W_{\psi pi}$ are set as:

$$QF\left(W_{\psi_{p_i}}\right)_{BCL} = \frac{1}{n}\sum_{j=1}^{k} W_{\psi_{p-j}} - 2 \cdot \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(t_{p-j} - \mu_{t_{p-j}}\right)^2} \tag{11}$$

$$TF\left(W_{\psi_{p_i}}\right)_{BCL} = \min\left(W_{\psi_{p-j}}\right) - \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(W_{\psi_{p-j}} - \mu_{W_{\psi_{p-j}}}\right)^2} \tag{12}$$

hence, incorporating boundary limits of eq. 4 and eq. 6 into reliability modelling, we get:

$$R\left(\psi_{WT_{p-j}}(t_j)\right) = f\left(\psi_{W_{p-j}}(t_j), \psi_{T_{p-j}}(t_j)\right) = \begin{cases} R\left(\psi_{T_{p-j}}(t_j)\right) = f\left(\psi_{T_{p-j}}(t_j)\right) \\ R\left(\psi_{W_{p-j}}(t_j)\right) = f\left(\psi_{W_{p-j}}(t_j)\right) \end{cases} \tag{13}$$

With logical operators, if both functional-productiveness of a machine to perform process t_{p-j} (eq. 6) and work W_{p-j} (eq. 8) in a specific period (T_j) will be defined as:

$$\psi_{WT_{p-j}} = f\left(\psi_{W_{p-j}}(t_j), \psi_{T_{p-j}}(t_j)\right) = \begin{cases} \psi_{WT_{p-j}} = 1, if \; \psi_{T_{p-j}} = 1 \wedge \psi_{W_{p-j}} = 1, \\ else \; \psi_{WT_{p-j}} = 0. \end{cases} \tag{14}$$

Hence, in the case of FPC, time to an event is not failure or stoppage of a machine but rather "outliers" or quasi-faults outside of the proposed dynamic boundary condition. Thus, the functional space is determined by the time to create a product (T_{pi}) and the work required (W_{pi}) from which one can determine the existence of quasi-failures.

IV. Comparative Functional Dynamics

A. Data Acquisition and Pre-Processing

A dataset of variables and raw data consists of sensor data, log data, and system degradation parameters/data. Simultaneously, the energy consumption is used to calculate reliability with the CFD approach (Fig. 3). In the domain of EBM practice, the data of CFD uses monitoring the ECP while considering faulty modes (e.g., temperature increase, leakage) and considering the actuator response (e.g., cylinder speed and force).

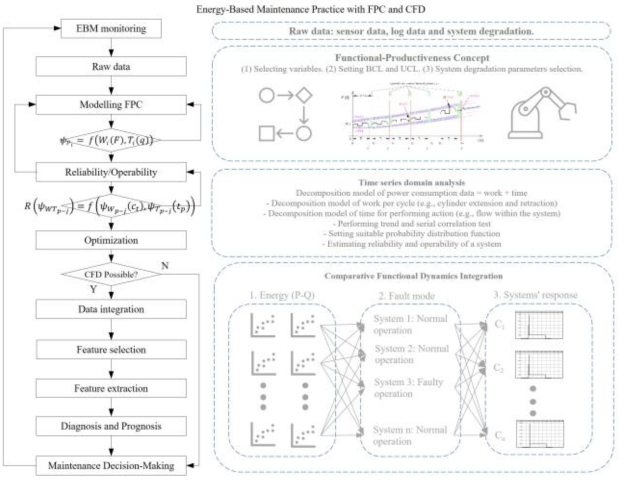

Fig. 3. Algorithm of Energy-Based Maintenance Practice with Functional-Productiveness concept and integrated Comparative Functional Dynamics with underlying activities of each step in the algorithm

The proposed model of EBM practice utilising FPC and CFD consist of the following steps: (1) developing FPC for a given machine (collecting raw data, modelling FPC and setting functionality boundary limits (eq.1-12)); (2) setting a functionality limits of monitoring energy variables is constructed on smoothing or moving average functions for quasi-faults in systems, suggesting that it needs a close examination if it continues to repeat with additional maintenance intervention (outliers set as Total Failure – TF in eq.5, eq.10, eq.12); (3) estimating operability and optimising maintenance interventions considering work and time for performing designed work in correspondence to functionality (eq.13-14); (4) CFD apparatus relies on ML tools (e.g., LDA, PCA) and uses flow and pressure as main indicators with machine response features (e.g., cylinder speed and force); (5) expected *outliers* in "normal" system operation are stored and used for feature extraction or penalising in the case of non-faulty disturbances in power transmission between elements (e.g., pump-valve-cylinder). These features of potential faulty conditions are modelled as a time to an event [0, 1].

Moreover, the primary goal of CFD is to eliminate quasi-disturbances by penalising non-faulty operating conditions, energy changes and deviation in actuator response by comparing multiple systems' ECPs, operational states and actuator responses. For instance, let us consider monitoring n hydraulic systems' pressure and flow data and comparing the data with actuator response (e.g., measuring cylinder variables – force and movement speed). By comparing multiple sensor readings between a single sensor disturbance and other n-1 sensor readings, one can easily conclude that the deviations are not due to chance. For instance, increased oil leakage in the hydraulic system will reduce a cylinder's force and movement speed.

V. Results and Discussion

A. *Survey Meta-Data*

Meta-data includes the type of manufacturing or service company's hydraulic machines applied and their associated characteristics (e.g., machines' age, working pressures and flows). However, only some important features are presented in Table II due to limited space.

TABLE II. Companies' and Machines' Meta-Data

Comp-n	Hydraulic Machines Meta-Data[b]						
	n	***Type***	***Fluid***	***MA***	***NWP***	***NWF***	***EC***
1.	22	IND	HV	11.9	106.3	45.7	10
2.	18	MOB	HV	8.3	276.5	141.3	80
3.	17	MOB	HV	10.2	186.4	122.7	50
4.	10	IND	HM	8.4	135.3	38.0	10
5.	18	MOB	HV	8.8	175.4	232.1	78
…							
72.	73	MOB	HV	6.8	291.8	175.4	85
Average	-	-	-	9.63	175.5	89.88	33.96

b. Type of industrial machines – Industrial -IND or Mobile – MOB; Fluid type based on ISO H-; Machine Age (MA); Nominal Working Pressure (NWP); Nominal Working Flow (NWF), Energy Consumption (EC) in kWh in average values of electric motor or ICE; Company number (Comp-n)

Besides the meta-data of companies and machines utilising hydraulic control systems, data also includes maintenance practices applied within companies. Likewise, associated maintenance practice includes activities of which the most important ones are given in Table III.

TABLE III. Maintenance Practice Meta-Data

Comp-n	Maintenance Practice Meta-Data[c]						
	MPPM	***MDT***	***MP***	***MAP***	***FAP***	***CMI***	***FRT***
1.	1.45	TECH	CM	VI	TECH	None	951
2.	0.44	TECH	OM	CC	TECH	PFTC	2432
3.	0.76	TENG	PM	UOA	BSc	PFTC	259
4.	0.30	None	CM	VI	None	None	2886
5.	0.33	TESP	PdM	OCM	MSc	PFTC	668
…							
72.	0.36	TENG	PM	UOA	BSc	PFTC	1087
Average	0.53	-	-	-	-	-	1157

c. MPPM – Maintenance Personnel Per Machine; MDT – Maintenance Department Team (TECH – Technicians; TENG – Technicians&Engineers; TESP – Technicians&Engineers&Specialists); MAP – Maintenance Analysis Program (VI – Visual inspection; CC – Contamination Control; UOA – Used Oil Analysis; OCM – Oil Condition Monitoring); FAP – Failure Analysis Personnel (TECH – Technician performs failure analysis; BSc – Engineer; MSc – Master engineering/specialist performs failure analysis.

Moreover, data collected are sorted into technical machine operational characteristics, maintenance practice and maintenance performance parameters. The most important ones include MTBF, HFW, and EC. The values of MTBF (fig. 4) are taken from the database of companies that participated in the survey; HFW is divided by the number of machines and hours (fig. 5).

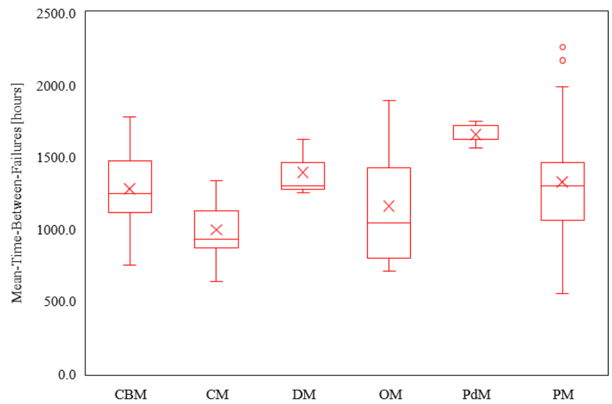

Fig. 4. Mean-Time-Between-Failures concerning maintenance policy

Hydraulic power waste is calculated as non-random deteriorating failure concerning leakages from selected systems reported stopped due to the same loss. The results show that around 21% of stoppages attribute to leakage due to degradation of elements, seals, places of connection between pipes and tubes, or random operator faults leading to the breakage of components. For calculating energy losses due to leakage, approximations ranging from 1,1-2% [55], [56] are used for calculations.

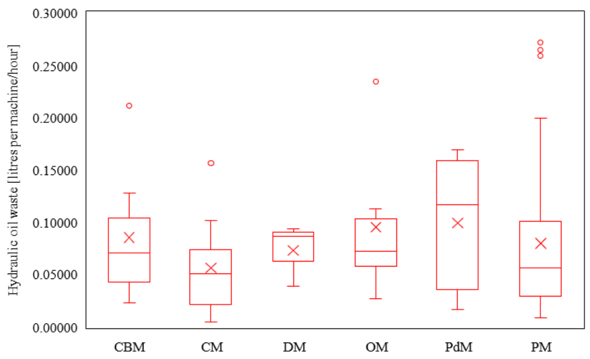

Fig. 5. Hydraulic fluid waste per machine/hour concerning maintenance policy

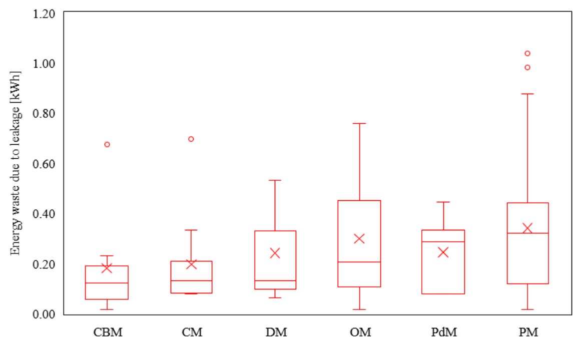

Fig. 6. Hydraulic power waste per machine/hour concerning maintenance policy

B. Comparison of EBM with Traditional MPs

The collected parameters in Table IV are given for objective assessment of the results obtained. Since only two technicians are responsible for managing and maintaining hydraulic bulldozers, it still shows a higher average

personnel per machine than other MPs. The bulldozers' age is also lower than the average values of hydraulic machines subjected to different MPs. Filter management (FRT) is conducted appropriately and corresponds to CBM and PdM practice. However, data shows bias towards observing machinery, including more inspections and improved monitoring by personnel.

TABLE IV. PROPERTIES OF EBM AND TRADITIONAL MPS

Prop.	**Type of Maintenance Practice**[d]						
	EBM	***CM***	***PM***	***OM***	***DM***	***CBM***	***PdM***
MPPM	0.66	0.34	0.48	0.47	0.15	0.45	0.65
MA	5.50	9.49	9.15	11.22	8.50	11.74	9.01
FRT	501	993	796	773	1196	636	484

d. MPPM – Maintenance Personnel Per Machine; MA – Machine Age; FRT – Filter Replacement Time [hours];

Table V provides data from simulated EBM maintenance practices compared to other maintenance practices, and the results show the following. The MTBF of hydraulic machines subjected to EBM practice resulted in $\mu \pm \sigma = 778.27 \pm 389.81$ hours, which ranges from -22% to -53% worse performance in comparison to other maintenance practices given in Table V, respectively. Although, as stated, some quasi-failures requesting stoppage are censored and did not show failure after inspection. Energy consumption per hour showed better performance than any other practice, best in the case compared to PM practice (113%), while CBM shows the least, although still 20% higher.

TABLE V. PERFORMANCE HEATMAP OF EBM VS TRADITIONAL MPS

	Maintenance Practice (Policy)[e]					
EBM	***CM***	***PM***	***OM***	***DM***	***CBM***	***PdM***
MTBF	-22%	-41%	-33%	-44%	-39%	-53%
EC-L	46%	113%	101%	60%	20%	60%
HFW	50%	112%	154%	95%	127%	165%

e. MTBF – Mean Time Between Failures; EC-L – Energy Consumption due to Leakage [kW/oil leakage * hour]; HFW – Hydraulic Fluid Wasted per machine [l/hour].

Hydraulic fluid waste (HFW) per hour provides interesting information. Although some data from the survey includes monthly overall hydraulic fluid waste per machine, data is obtained by transforming it into oil waste per machine hour for a given system. Although expected, EBM outperformed CM, PM, OM, and DM in terms of oil preservation and not disposing nor resulting in abnormal leakage; the comparison to CBM and PdM practice shows 127% and 165% reduction in fluid waste, thus, requiring further and in-depth analysis for such an anomaly.

Several assumptions can be drawn. Firstly, those machines subjected to CBM and PdM policies may follow equipment manufacturers' recommendations and replace the oil every 1000h resulting in such huge fluid waste. Secondly, depending on the environmental requirements, the fluid is constantly replaced in the same manner. In both cases, the primary goal is to maintain the machine in an operational state as long as possible; however, oil can still have good working characteristics even after disposal. Thirdly, maintenance management and personnel do not consider leakage a serious threat and neglect the obvious environmentally hazardous effect.

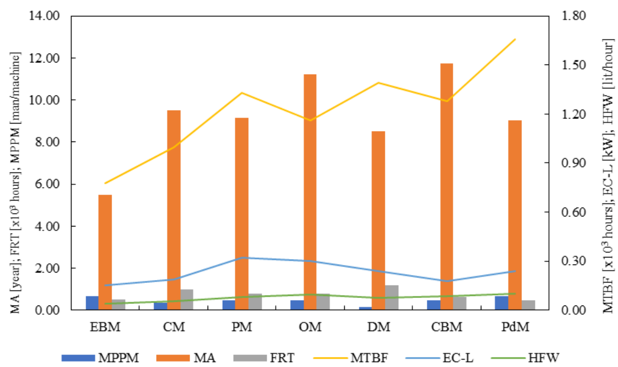

Fig. 7. Characteristics and performances of various maintenance practices

The evidence suggests the following from analysing activities and performance of each maintenance practice (fig. 7). MTBF negatively correlates with the machine age, confirmed by the previous study [54]. Following original equipment manufacturers' guidelines, presumably, technicians and managers within CBM and PdM paradigm dispose of the hydraulic oil while still possessing good physio-chemical characteristics; however, needing further analysis to support such claims. Although CBM and PdM show improvement in energy efficiency and reduction in energy waste, the EBM outperforms both practices; however, the EBM practice requires constant inspection.

VI. Concluding Remarks

Finally, this work provides meta-data on maintenance practices applied within industrial and mobile hydraulic machines. Although some organisations claim to utilise PdM policy, they lack the proper technical and technological apparatus to support such claims. Collected data from a survey on West Balkan territory compared with the newly proposed maintenance practice of EBM. The basic idea of EBM is to monitor energy consumption and deviations in the signal to detect anomalies; thus, system faults and react upon them before potential failure. The idea of changing the functionality into FPC helped enable EBM. However, FPC itself could not fulfil the demands because the concept had problems detecting faulty from non-faulty conditions; therefore, another idea is introduced as comparative functional dynamics. The substance behind the CFD is to monitor system response from the system being analysed and other systems with the same characteristics. This way, potential "outliers" and errors can be reduced, thus increasing the accuracy of detecting faults. As a result, the simulation of an implemented EBM practice on three bulldozers resulted in reduced oil and energy waste, however, at the cost of more inspection and increased stoppages.

When writing the paper, several papers are concerned with monitoring energy as a consumption parameter and a fault recognition pattern [57], stressing that this could resonate with a zeitgeist, especially with environmental legislation and initiatives imposition (e.g., Green Deal). Overall, the EBM suggests measuring the quality of energy response because production depends on actuator response (e.g., hydraulic press – cylinder speed and force), which again depends on volumetric flow and pressure.

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