UNIVERSITY OF NOVI SAD

FACULTY OF TECHNICAL SCIENCES

THE CONCEPT OF FUNCTIONAL-PRODUCTIVENESS FOR MODELLING RELIABILITY IN ENERGY-BASED MAINTENANCE DOMAIN

DOCTORAL DISSERTATION

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Novi Sad, 2022.

УНИВЕРЗИТЕТ У НОВОМ САДУ
ФАКУЛТЕТ ТЕХНИЧКИХ НАУКА

КОНЦЕПТ ФУНКЦИОНАЛНЕ ПРОДУКТИВНОСТИ ЗА МОДЕЛОВАЊЕ ПОУЗДАНОСТИ У ДОМЕНУ ОДРЖАВАЊА ЗАСНОВАНОМ НА ЕНЕРГИЈИ

ДОКТОРСКА ДИСЕРТАЦИЈА

Ментор: Др Митар Јоцановић

Кандидат: Орошњак Марко

Нови Сад, 2022.

УНИВЕРЗИТЕТ У НОВОМ САДУ ОБРАЗАЦ – 5а

НАВЕСТИ НАЗИВ ФАКУЛТЕТА ИЛИ ЦЕНТРА

КЉУЧНА ДОКУМЕНТАЦИЈСКА ИНФОРМАЦИЈА[1]

Врста рада:	Докторска дисертација
Име и презиме аутора:	Марко Орошњак
Ментор (титула, име, презиме, звање, институција)	др Митар Јоцановић, редовни професор, Факултет техничких наука Нови Сад
Наслов рада:	Концепт функционалне продуктивности за моделовање поузданости у домену одржавања заснованом на енергији
Језик публикације (писмо):	Енглески (латиница)
Физички опис рада:	Унети број Страница: 217 Поглавља: 12 Референци: 145 Табела: 84 Слика: 148 Прилога: 14
Научна област:	Индустријско инжењерство и инжењерски менаџмент
Ужа научна област (научна дисциплина):	Квалитет, ефективност и логистика
Кључне речи / предметна одредница:	индустријско инжењерство, предиктивно одржавање, енергетски засновано одржавање, анализа поузданости, хидраулички систем, уљна анализа, праћење стања флуида, контрола контаминације, машинско учење, анализа главних компоненти, неуронске мреже, логистичка регресија, дрво одлучивања
Резиме на српском језику:	Примена политике Енергетски Заснованог Одржавања (ЕЗО) код производних компанија чини теоретску поузданост ненасумичних отказа релативно ниском. Међутим, све је већа присустност лоше праксе одржавања и ниске тржишна интелигенције која се јавља у истраживању. Иако се различите праксе одржавања примењују, укључујући концепте одржавања по стању и предиктивног одржавања, резултати показују да перформансе варирају у складу са политиком доношења одлука на свим нивоима одлучивања. Разлози за овакве премисе намећу три стуба доказа:

[1] Аутор докторске дисертације потписао је и приложио следеће Обрасце:
5б – Изјава о ауторству;
5в – Изјава о истоветности штампане и електронске верзије и о личним подацима;
5г – Изјава о коришћењу.
Ове Изјаве се чувају на факултету у штампаном и електронском облику и не кориче се са тезом.

	(1) стање пројеката; (2) стање литературе; и (3) стање праксе. Докторант користи ове доказе као апарат да би се оправдао недостатак утицаја одржавања и постигнућа у индустријском „четвртом таласу". За сваки дати стуб доказа дат је детаљан опис протокола. Главни недостаци напретка се огледају кроз доношење одлука с обзиром да се већина научника и инжењера ослања на статичке податке приликом одлучивања. Чини се да примена праксе предиктивног одржавања манифестује потешкоће приликом прелаза са статичких на динамичке податке. Ове потешкоће се огледају кроз лоше доношење одлука од стране топ менаџмента. Застарели оквири одржава по стању на које се произвођачи ослањају не пружају дугорочне ефекте, посебно у предстојећој одрживој производњи. Обухватајући одрживу производњу као једну од кључних технологија развоја и индикаторе одрживости као алат(и) праћења стања који се ослањају на енергетске и еколошке динамичке индикаторе, доношење одлука у одржавању се разликује између традиционалних политика одржавања и политике одржава заснованом на енергији. Недостаци конвенционалних алата праћења стања (нпр. виброакустика) је што се такви индикатори не могу применити на вишим нивоима одлучивања ван оперативног (стратешки и тактички). С обзиром да се праћење расипања енергије (као што је виброакустика) користи као индикатор за дијагностику и прогностику, употреба индикатора примарне енергије (нпр. проток и притисак, струја и напон) може да се користи и као дијагностички и прогностички индикатор, али такође и као индикатор за оптимизацију одржавања и као монетарна вредност јер потрошња енергије може лако да се финансијски прикаже. Тренутни еколошки оквири и нормативи енергетске ефикасности, према томе, подржавају претходно поменуту праксу одржавања засновану на енергији. Аутор тезе има за циљ да предложи концепт функционалне продуктивности (ФП) као квантитативну процену приликом разграничења функционалног од не-функционалног система. Друго, коришћењем алгоритама машинског учења за бинарну класификацију, циљ је да се одреди класификација за системе који задовољавају функциналност од система који то не чине ослањајући се на маркере функционалне продуктивности. Ови маркери су преузети из модела ослањајући се на битност променљиве приликом класификације у датом хипотетичком простору. Ови маркери (променљиве) се затим могу користити као индикатори за оптимизацију одређивањем поузданости система при чему се доприноси одлучивању у примењеној пракси одржавања. Употреба практичног хидрауличког система машине за производњу гуме, успешно је примењена класификација за предложене циљеве. Аутор тезе је применио моделе машинског учења (на енгл. *Gaussian naïve Bayes GNB, Artificial Neural Networks – ANN, Logistic Regression – LR, Classification and Regression Tree – CART, and k-Nearest Neighbour kNN*) за класификацију, где је највиша прецизност постугнута са моделима неуронских мрежа изнад 95% узимајући у обзир податке који нису били раније доступни.
Датум прихватања теме од стране надлежног већа:	
Датум одбране: (Попуњава одговарајућа служба)	
Чланови комисије: (титула, име, презиме, звање, институција)	**Председник:** др Иван Бекер, редовни професор, Факултет техничких наука Нови Сад, Универзитет у Новом Саду, Србија

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KEY WORD DOCUMENTATION[2]

Document type:	Doctoral dissertation
Author:	Orošnjak Marko
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Subject, Key words:	industrial engineering, predictive maintenance, energy-based maintenance, reliability analysis, hydraulic systems, oil analysis, fluid condition monitoring, contamination control, supervised machine learning, unsupervised machine learning, principal component analysis, artificial neural networks, k-nearest neighbours, logistic regression, decision tree, classification and regression tree, support vector machine
Abstract in English language:	Applying the Energy-Based Maintenance (EBM) policy within manufacturing companies, the theoretical probability of non-random deteriorating failures is relatively low. However, poor industrial maintenance practices and market intelligence have been reported. Nonetheless, although various maintenance practices, including CBM (Condition-Based Maintenance) and PdM (Predictive Maintenance) concepts, are applied within manufacturing sectors, results show that performance differs with decision-making and policy-making in all layers of abstraction. The reasons for such propositions are imposed by three main pillars of evidence, namely (1) state-of-the-projects, (2) state-of-the-literature, and (3)

[2] The author of doctoral dissertation has signed the following Statements:
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	state-of-the-practice. The author of the thesis uses this evidence as an apparatus for justifying the lack of maintenance impact and achievement in the industrial "4th Wave". A specific in-detail description of the protocol is given for each given pillar. The lack of achievement are seen in decision-making since most engineers and scientists rely on static data-driven approaches. Utilising the PdM practice seems to exhibit difficulties in switching from a static to a dynamic data-driven approach. The setbacks are seen through the poor decision-making of top management. Hence, the outdated CBM frameworks that manufacturers rely upon fall short of providing long-term effects, especially in upcoming sustainable manufacturing. Encompassing sustainable manufacturing as one of the key enabling technologies (KET) and sustainability indicator(s) as a condition monitoring (CM) tool(s) that rely on energy and environmental dynamics, maintenance decision-making (MDM) differs between traditional maintenance practice and EBM practice. The setbacks of conventional CM tools (e.g. vibrational and acoustic) seem to be facing difficulties while being outside of operational decision-making layer (strategic and tactical). Since monitoring energy dissipation (e.g., vibroacoustics) is used as a diagnostic and prognostic indicator, the use of primary energy indicators (e.g., flow and pressure, current and voltage) can be used as both a diagnostic and prognostic indicator, but also as an indicator for maintenance optimisation and monetary value because energy consumption can be easily represented financially. The ongoing sustainability frameworks and energy efficiency normatives, therefore, support aforemtioned practice over traditional ones. The author of the thesis is set to propose the functional-productiveness (FP) concept as a quantitative estimate in delineating functional from non-functional labels. Secondly, using machine learning (supervised and unsupervised) algorithms for binary classification, the goal is to determine the healthy from the non-healthy state by relying upon functional-productiveness markers (FPMs). These markers are extracted from classification hypothesis space by variable importance; as such can be used for establishing the reliability of systems and contributing to maintenance decision-making. Using a practical hydraulic control system of a rubber mixing machine, it was possible to establish high classification accuracy between healthy and non-healthy states. The author used: Gaussian naïve Bayes (GNB), Artificial Neural Networks (ANN), Logistic Regression (LR), Classification and Regression Tree (CART), and k-Nearest Neighbour (kNN) for classification, where ANN resulted in the highest classification accuracy (95%) given unseen data.
Accepted on Scientific Board on:	
Defended: (Filled by the faculty service)	
Thesis Defend Board: (title, first name, last name, position, institution)	**Chairman:** dr Ivan Beker, full professor, Faculty of Technical Sciences Novi Sad, University of Novi Sad, Serbia **Member:** dr Sandra Ramos, associate professor, Instituto Superior de Engenharia do Porto, Instituto Politécnico do Porto, Portugal **Member:** John K. Duchowski, director of institute HYDAC FluidCareCenter GmbH, Sulzbach/Saar, Germany **Member:** Dr Milan Delić, associate professor, Faculty of Technical Sciences Novi Sad, University of Novi Sad, Serbia **Member:** dr Velibor Karanović, professor, Faculty of Technical Sciences Novi Sad, University of Novi Sad, Serbia

	Mentor: dr Mitar Jocanović, full professor, Faculty of Technical Sciences Novi Sad, University of Novi Sad, Serbia

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I would also like to express my gratitude for having friends and relatives sticking with me throughout this stressful time. I would like to thank each one of you for putting up with me and carrying the weight of this work with me. I would like to express my deepest and the most honest love and gratitude to my closest friends and family.

To my wonderful mother Milica, who taught me how to be a more gentle and loving person. To my father Dragan, who showed me how to be more disciplined and consistent. To my sister Vanja, who filled me with joy and happiness. Thank you all for understanding me and for giving me emotional support throughout these last seven years.

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I love you from the bottom of my heart!

"*The object in life is not to be on the side of the majority, but to escape finding oneself in the ranks of the insane.*"

Marcus Aurelius

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ACRONYMS

ABAO	As-bad-as-old
ACF	Autocorrelation function
AGAN	As-good-as-new
AI	Artificial Intelligence
AMSAA	Army Materials Systems Analysis Activity
ANN	Artificial Neural Network
AR	Autoregressive
AR(I)MA	Autoregressive moving average (I* as integrated)
CBM	Condition-Based Maintenance
CD	Censor Data
CM	Condition Monitoring
CNN	Convolutional Neural Networks
CORDIS	Community Research and Development Information Service
CR	Closely-related
CrM	Corrective Maintenance
EBM	Energy-Based Maintenance
EC	Exclusion Criteria
ENG	English language criteria
FBM	Failure-Based Maintenance
FD	Failure Data
FN	False-negative
FP	False-positive
FPM	Functional-productiveness marker
FPP	Framework Programme projects
FT	Full-text

FTP	Full-text paper
GUB	Greatest upper bound
HUB	Highest Upper Bound
IC	Inclusion Criteria
KET(s)	Key Enabling Technologie(s)
K-means	Kernel means clustering technique
KPI(s)	Key Performance Indicator(s)
LCL	Lower Control Limit
LOCF	Last observation carried forward
LogR	Logistic Regression
LR	Losely related
LUB	Least Upper Bound
LUB	Least upper bound
MA	Moving average
MAR	Missing at random
MCAR	Missing completely at random
MDM	Maintenance Decision-Making
MDML(s)	Maintenance Decision-Making Level(s)
ML	Machine Learning
MNAR	Missing not at random
MPI(s)	Maintenance Performance Indicator(s)
MRL	Mean Residual Life
MTBF	Mean-time-between-failures
MTTF	Mean-time-to-failure
MTTR	Mean-time-to-repair
NN	Neural Networks
NOCB	Next observation carried backwards

NR	Non-related
OPS	Original peer-review study
PACF	Partial autocorrelation function
PCA	Principal Component Analysis
PCR	Principal Component Regression
PdM	Predictive Maintenace
PEC	Projects funded by EU/EC
PM	Preventive Maintenance
PR	Partially-related
ROCOF	Rate of Occurrence of Failures
RoP	Repository of Projects
RTF	Run-to-failure
RUL	Remaining Useful Life
SCADA	Supervisory Control And Data Acquisition
SMPI(s)	Sustainable Maintenance Performance Indicator(s)
SVM	Support Vector Machine
TBF	Time-between-failures
TBR	Time-between-repairs
TD	Truncated Data
TF	Time frame
TN	True negative
TP	True positive
TTF	Time-to-failure
TTR	Time-to-repair
UCL	Upper Control Limit

ABSTRACT

Applying the Energy-Based Maintenance (EBM) policy within manufacturing companies, the theoretical probability of non-random deteriorating failures is relatively low. However, poor industrial maintenance practices and market intelligence have been reported. Nonetheless, although various maintenance practices, including CBM (Condition-Based Maintenance) and PdM (Predictive Maintenance) concepts, are applied within manufacturing sectors, results show that performance differs with decision-making and policy-making in all layers of abstraction. The reasons for such propositions are imposed by three main pillars of evidence, namely (1) state-of-the-projects, (2) state-of-the-literature, and (3) state-of-the-practice. The author of the thesis uses this evidence as an apparatus for justifying the lack of maintenance impact and achievement in the industrial "4th Wave". A specific in-detail description of the protocol is given for each given pillar. The lack of achievement are seen in decision-making since most engineers and scientists rely on static data-driven approaches.

Utilising the PdM practice seems to exhibit difficulties in switching from a static to a dynamic data-driven approach. The setbacks are seen through the poor decision-making of top management. Hence, the outdated CBM frameworks that manufacturers rely upon fall short of providing long-term effects, especially in upcoming sustainable manufacturing. Encompassing sustainable manufacturing as one of the key enabling technologies (KET) and sustainability indicator(s) as a condition monitoring (CM) tool(s) that rely on energy and environmental dynamics, maintenance decision-making (MDM) differs between traditional maintenance practice and EBM practice. The setbacks of conventional CM tools (e.g. vibrational and acoustic) seem to be facing difficulties while being outside of operational decision-making layer (strategic and tactical). Since monitoring energy dissipation (e.g., vibroacoustics) is used as a diagnostic and prognostic indicator, the use of primary energy indicators (e.g., flow and pressure, current and voltage) can be used as both a diagnostic and prognostic indicator, but also as an indicator for maintenance optimisation and monetary value because energy consumption can be easily represented financially. The ongoing sustainability frameworks and energy efficiency normatives, therefore, support aforemtioned practice over traditional ones.

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keywords: industrial engineering, predictive maintenance, energy-based maintenance, reliability analysis, hydraulic systems, oil analysis, fluid condition monitoring, contamination control, supervised machine learning, unsupervised machine learning, principal component analysis, artificial neural networks, k-nearest neighbours, logistic regression, decision tree, classification and regression tree, support vector machine

Резиме

Примена политике Енергетски Заснованог Одржавања (ЕЗО) код производних компанија чини теоретску поузданост ненасумичних отказа релативно ниском. Међутим, све је већа присутност лоше праксе одржавања и ниске тржишна интелигенције која се јавља у истраживању. Иако се различите праксе одржавања примењују, укључујући концепте одржавања по стању и предиктивног одржавања, резултати показују да перформансе варирају у складу са политиком доношења одлука на свим нивоима одлучивања. Разлози за овакве премисе намећу три стуба доказа: (1) стање пројеката; (2) стање литературе; и (3) стање праксе. Докторант користи ове доказе као апарат да би се оправдао недостатак утицаја одржавања и постигнућа у индустријском „четвртом таласу". За сваки дати стуб доказа дат је детаљан опис протокола. Главни недостаци напретка се огледају кроз доношење одлука с обзиром да се већина научника и инжењера ослања на статичке податке приликом одлучивања.

Чини се да примена праксе предиктивног одржавања манифестује потешкоће приликом прелаза са статичких на динамичке податке. Ове потешкоће се огледају кроз лоше доношење одлука од стране топ менаџмента. Застарели оквири одржава по стању на које се произвођачи ослањају не пружају дугорочне ефекте, посебно у предстојећој одрживој производњи. Обухватајући одрживу производњу као једну од кључних технологија развоја и индикаторе одрживости као алат(и) праћења стања који се ослањају на енергетске и еколошке динамичке индикаторе, доношење одлука у одржавању се разликује између традиционалних политика одржавања и политике одржава заснованом на енергији. Недостаци конвенционалних алата праћења стања (нпр. виброакустика) је што се такви индикатори не могу применити на вишим нивоима одлучивања ван оперативног (стратешки и тактички). С обзиром да се праћење расипања енергије (као што је виброакустика) користи као индикатор за дијагностику и прогностику, употреба индикатора примарне енергије (нпр. проток и притисак, струја и напон) може да се користи и као дијагностички и прогностички индикатор, али такође и као индикатор за оптимизацију одржавања и као монетарна вредност јер потрошња енергије може лако да се финансијски прикаже. Тренутни еколошки оквири и нормативи енергетске ефикасности, према томе, подржавају претходно поменуту праксу одржавања засновану на енергији.

Аутор тезе има за циљ да предложи концепт функционалне продуктивности (ФП) као квантитативну процену приликом разграничења функционалног од не-функционалног система. Друго, коришћењем алгоритама машинског учења за бинарну класификацију, циљ је да се одреди класификација за системе који задовољавају функциналност од система који то не чине ослањајући се на маркере функционалне продуктивности. Ови маркери су преузети из модела ослањајући се на битност променљиве приликом класификације у датом хипотетичком простору. Ови маркери (променљиве) се затим могу користити као индикатори за оптимизацију одређивањем поузданости система при чему се доприноси одлучивању у примењеној пракси одржавања. Употреба практичног хидрауличког система машине за производњу гуме, успешно је примењена класификација за предложене циљеве. Аутор тезе је применио моделе машинског учења (на енгл. *Gaussian naïve Bayes GNB, Artificial Neural Networks – ANN, Logistic Regression – LR, Classification and Regression Tree – CART, and k-Nearest Neighbour kNN*) за класификацију, где је највиша прецизност постугнута са моделима неуронских мрежа изнад 95% узимајући у обзир податке који нису били раније доступни.

кључне речи: индустријско инжењерство, предиктивно одржавање, енергетски засновано одржавање, анализа поузданости, хидраулички систем, уљна анализа, праћење стања флуида, контрола контаминације, машинско учење, анализа главних компоненти, неуронске мреже, логистичка регресија, дрво одлучивања

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Chapter I

"*I saw no way the heavens were stitched!*"
Emily Dickinson

1 INTRODUCTION

The thesis' contextual setting starts by explaining the technological landscape in which industrial maintenance finds itself in the era of Industry 4.0. The implication of such an idea is not only to shed light on maintenance as a science and a discipline within the technological "4th Wave" but also to portray the diachronic nature of maintenance' evolvement synthesised from three pillars: (1) projects; (2) practice and (3) literature. Within the proposed pillars of evidence, the first milestone consists of collecting meta-data and reflecting the state-of-the-art maintenance manifesto. To avoid adding another horizontal-type research statement circulating around the same ideology, the author of the thesis aims to switch focus from the general notion of systems' (or machines') time- and condition-based maintenance (CBM) towards sustainable energy-oriented practice. The substance behind the argument will be explained through rationale, aims, and objectives to gain a clearer insight into the issues being addressed.

1.1 RESEARCH MOTIVATION AND RATIONALE

1.1.1 INNOVATION AND MAINTENANCE

As the pursuit of innovation has inspired scientists and industrialists, it also provoked critics who suspect that peddlers of innovation radically overvalue innovation and that what happens after innovation is more important [1]. Unquestionably, the body of innovation embraced by digitalisation (i.e. digital transformation) showed more technological progress in the last twenty years than ever before. In line with such a dominant cult, manufacturing and service companies started providing novel and mass customised market-oriented solutions overlooking innovation's disruptive nature at the time. New internet architectures and autonomous learning tools (e.g., Deep Learning) drove success in fulfilling market demands exponentially faster. As such, altered business models and organisational assets provided new ways of responding to customer demands in a more agile and rewarding manner. This ongoing transformation of industrial assets and expansion of technology-/market-driven solutions eventually coined the term "Industry 4.0" (I4.0). However, in such a flustering manner of accomplishing customer needs, where production and service systems rapidly change their production flows, the degree to which industrial maintenance managed to keep pace is the real question.

As asset-intensive companies set their agendas in accomplishing high-end market demands utilising Big Data analytics (e.g. Machine Learning, Cloud Computing), predicting and responding to disruptive market demands became much more manageable. One would expect that maintenance as an "operational-dependent servant" can carry the weight of new technology while upholding the imposed effectiveness and subdue to environmental legislation set by the political agendas, such as Green Deal targets [2]. The perception of "necessary evil" as maintenance is usually perceived by small- to medium-sized enterprises (SMEs) and service firms as reluctant to invest in maintenance improvement; the implications stay the same—unclear benefits and scarce investments into maintenance research. Interestingly, 83% of high-tech companies plan to invest in predictive maintenance [3], claiming that it should be perceived as a profit-generating function [4] and, in some cases, even a value-creating factor [5], which leaves one in a state of cognitive dissonance, consequently shattering and contradicting the beliefs of SMEs.

By predominantly favouring maintenance optimisation over the last few decades [6], it seems like the malleable nature of maintenance research falls short of advancing into I4.0. Some question industrial maintenance's ability to evolve without intruding into the operational part of the system, and others turn attention to reviewing existing maintenance literature for a potential research gap [7]. Both, however, follow the imposed ideology of I4.0 without changing or altering maintenance constructs.

Although the I4.0 feels like a driver of intellectual creativity of smart factories and new business models on one side, however, recently felt like a philosophical stance and a buzzword in domains other than industry-oriented solutions for justifying proposed novel concepts' or, in the case of high-tech academia, a way to make a scientific footprint by latching on the emblem of Industry 4.0. Consequently, a blurred sensation of maintenance advancements, saturation in secondary source literature, and underachievements of original scientific contributions in changing the maintenance constructs are poorly perceived. Even though the industrial "4th wave" technological advancements show immense progress, they rely on fundamental energy transformation and control principles. This could be one of the strongest arguments why maintenance stood in the way of progress and which is one, among others, the reason to step back to an energy-oriented solution. Altering maintenance constructs and re-defining maintenance indicators on energy preservation/transformation could be a much-needed paradigm shift. Let us elaborate on the trade-off between primary energy and waste energy depicted by the *p-f* curve in the following.

1.1.2 ENERGY AS A CONDITION MONITORING INDICATOR AND THE P-F CURVE

Traditional monitoring signals of the *p-f* curve (e.g., sound, temperature, vibration) are condition monitoring indices of machine health that signal potential degradation (e.g., wear). The traditional *p-f* curve (red line Figure 1) shows that the main signals for measuring machine health (e.g., temperature, vibration) are consequences of energy waste that are being monitored. The thesis's idea is to replace these waste signals with the primary energy source from which work is being done. Namely, if one understands that energy, i.e., the capacity to do work, transforms from one type to another, then there is no degradation but the change of potential energy and kinetic energy (capacity and transfer). Therefore, the inference is that the maintenance job is not preventing "degradation" per se but preserving potential and kinetic energy. It is meant to preserve the primary energy source, whether potential or kinetic form, by preventing degradation. For instance, the hydraulic pump has its potential energy defined by optimal (and maximum) volumetric capacity (cm^3) and rotational speed (rpm), with a defined ratio of losses (η_Σ) consisting of volumetric, hydraulic and mechanical losses. By defining the input parameters, the maintenance technician's task is to preserve this potential energy or prolong it as much as possible by various tasks, for instance, preserving the mechanical structure of a pump by preventing physical change (damage) that can lead to reducing primary energy transfer through fluid via external and internal pump leakage. Therefore, the damage is seen by making more than one fluid-energy output source. By observing the kinetic energy of a hydraulic system, the focus is then on hydraulic fluid since it carries the energy from the pump to the actuators. Therefore, to prevent the loss of hydraulic energy of a fluid, it needs to be cooled, cleared of contaminants (e.g., water, solid particles, air) and properly preserved considering its chemical properties (e.g., base and additives) for maintaining its properties – viscosity, compressibility, wear resistance, thermal stability, and many others. The question imposed at the start is, how is this related to the p-f curve?

The basic signals being monitored are that the focus is given more to energy waste (red line Figure 1) than to primary-energy usage patterns (green line Figure 1) for the same goal of detecting signal anomalies. Hence, the motivation of the thesis is spurred by the lack of condition monitoring apparatus for making decisions based on the primary energy consumption (transformation), particularly flow and pressure derived from or to hydraulic power, which are used as indicators in this thesis. The important notice is that the author is not elbowing out traditional condition monitoring analytics, nor is it possible to replace it soon. Instead, the general idea of monitoring hydraulic power is to establish markers (classifying healthy from the non-healthy system) that result from the inner or outer stressors. Monitoring hydraulic power change from the input to the output (whether a component or the system) is a health index marker representing the quality of operational and maintenance performance and actions being taken. The benefits of observing the power change, i.e., the rate at which energy is transferred, are multiple. For instance, it can be used for diagnostic and prognostic purposes – for establishing the health index of a machine, system or unit, or predicting degradational patterns and preventing or reducing them. Secondly, energy can be easily transformed into monetary value by monitoring degradation; operational and maintenance performance can be a cost marker. Thirdly, it can be a potential human health hazard indicator by observing the high peaks in hydraulic power caused, for instance, valve jamming. Finally, it can also be used as an environmental pollution indicator to calculate the emission due to energy usage and waste. Given the information, one can conclude that each indicator can be used as a threshold for stopping the system. Hence, the maintenance goal is no longer preserving machine functionality but multiple imposed functionality indices.

The maintenance research community is also entering the sustainability domain with the imposed government legislation and initiatives (e.g., the Green Deal). We are already witnessing reports proposing sustainable maintenance (SM). However, the author argues that the Energy-Based Maintenance (EBM) practice is more technically sound given all the acquired hindsight so far. There are a few downsides to why EBM is still not fully accepted. Firstly, available instruments (e.g., pressure and flow turbine) still do not have the sensitivity of instruments such as vibroacoustic ones. Hence, detecting signal deviations comes with a penalty and delay. Secondly, it includes top decision-making and their poor understanding that energy is the primary currency of the work. The third reason includes technical and data reasoning, which strongly depends on market intelligence and data processing capabilities, which begs a substantial question: "Is data science going to replace maintenance science?" Given the information, we only need a single phrase to epitomise the gap between maintenance and data science – ***functional-productiveness.***

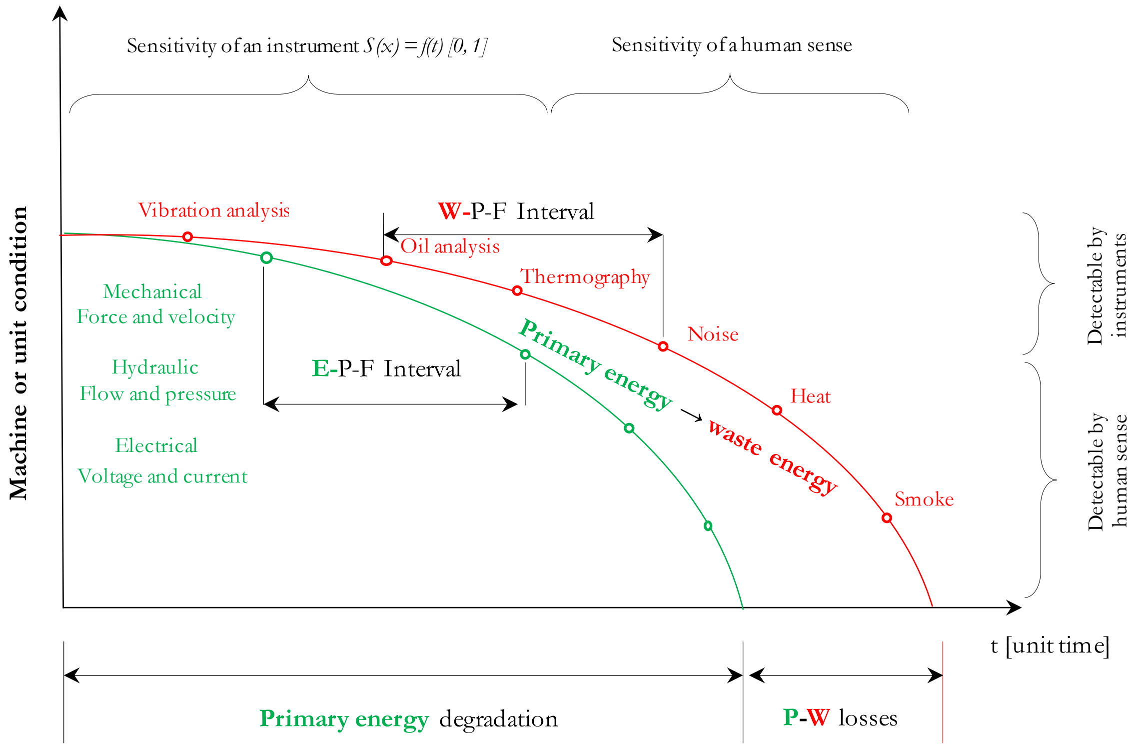


Figure 1. P-F curve of primary and waste energy description

1.1.3 PILLARS OF RATIONALE

As society enters the green (sustainable) manufacturing era, maintenance scholars exhaust the scope of existing theories and thrive for new ones within the economy's secondary sector. Even though manufacturing companies' principal aim is profit-driven, stoppages must be avoided at all costs; the advent of sustainability initiatives in the manufacturing sector resonates with the need for a more compelling approach. Although industrial maintenance has changed over the last half a century; however, it seems like the nature of maintenance evolution resembles static and sporadic shifts in the industrial landscape. This is reflected through the exponential rise of literature review studies and the ever-present need for a paradigm shift. The three main pillars of evidence that support the underlying reason for such a claim consist of: (1) state-of-the-projects, (2) state-of-the-literature, and (3) state-of-the-practice, and interrelated issues within those pillars (Figure 2).

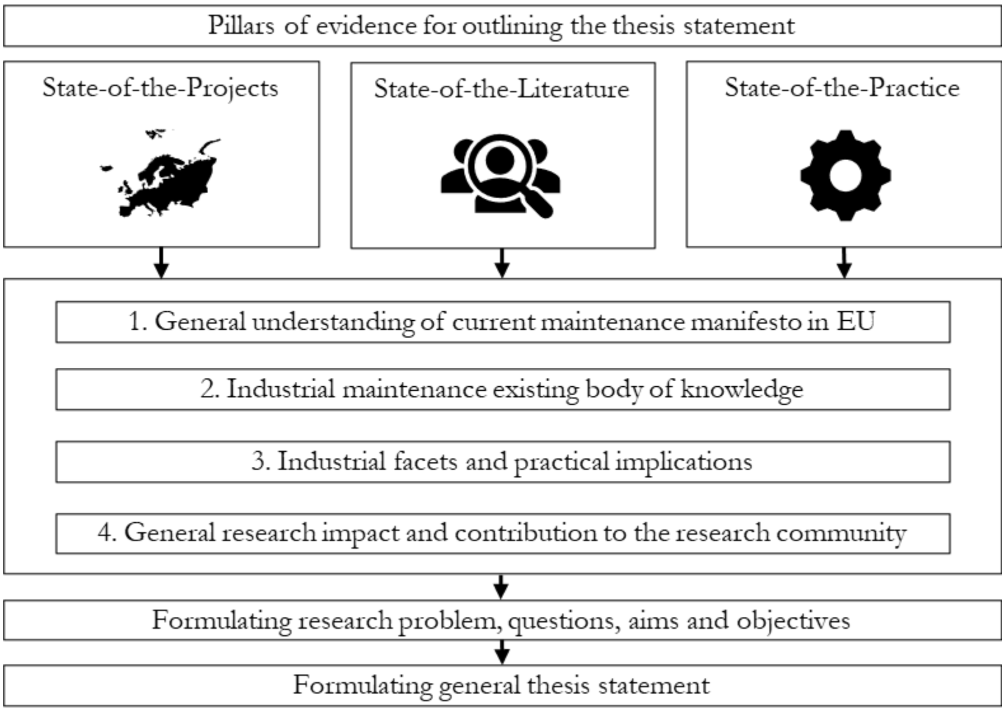


Figure 2. Pillars of research motivation and rationale

Conducting a literature review within the scope of maintenance studies, one cannot help but notice that maintenance scholars usually perceive the literature as the major driving source of evidence. Consequently, these propositional claims typically fall short of providing industry-accepted solutions, and they are rather considered simple explanatory remarks that are more phenomenological models or conditional presuppositions lacking sufficient validity in the industrial encirclement.

The author of the thesis argues that the literature is not enough large resource to portray the diachronic nature of maintenance in the last few decades. Therefore, a systematic review of available industrial maintenance projects within the EU should provide a more global understanding of the industrial maintenance manifesto as a scientific discipline.

Moreover, investigating industrial maintenance as a technological discipline is also necessary as a tradeoff between science and industrial practice to create a market-acceptable solution. Therefore, the questionnaire-based survey is developed to investigate the state of the practice. Both tasks for extracting evidence have not been done before by the author's knowledge and are considered beneficial for encapsulating the current body of knowledge in theory and practice.

1.1.4 BRIDGING THE GAP BETWEEN DATA AND MAINTENANCE SCIENCE

The opening keynote speaker at the COMADEM 2019 conference, professor Andrew Ball, warned against the claims that the future of maintenance could be left in the hands of data scientists [8]. Consequently, precluding its hypothetical existence and structural association with organisational needs in the eyes of policy-makers. Paradoxically, AI tools have the most significant impact in manufacturing by predominantly being used for Predictive Maintenance (PdM) [9], relying on control (process data) engineering rather than maintenance (failure data) engineering [10]. Examples of maintenance technology contorting into operational technology are already seen by the use of Statistical Process Control (SPC) tools as a part of intelligent monitoring for maintenance decision-making purposes [11]–[14]. However, failure (functional) boundaries of deteriorating systems cause problems for data scientists in predicting faults that are not pre-defined.

By neglecting the causes of system degradations, i.e., failure mechanisms, one could not appropriately manage a particular asset, which is why executives in asset-intensive industries state that failures and unplanned downtime are still the primary challenges to their business [15]. The fact that maintenance consumes from 40% [16], [17] to 60% [18] of operational activities questions whether maintenance is a cost or a profit-generating function [4]. Also, it raises doubts about whether data scientists can cope with random and non-random deteriorating mechanisms, thus, further justifying the need for more advanced Maintenance Performance Indicators (MPIs). However, traditional MPIs that include reliability, availability, maintainability and serviceability (RAMS) fall short of being used as a dynamic indication of condition monitoring benefits for zero-stoppage systems like aeroplanes and nuclear power plants. Enter operability.

What is meant by operability exactly? Although not so closely researched in the field of hydraulic systems' maintenance, it is explained mostly in the literature associated with the engine operability of aircraft propulsion systems. The goal of engine operability defined by Steenken [19] states "…*is to assure that the engine operates free of instability or with an acceptably small number of recoverable aerodynamic instabilities…"*. The evolution of operability from RAMS [20] towards today's understanding of the concept as "…*the ability to keep the system in a safe and reliable functioning condition*" suggests the starting point made – transferring from static (failure) data to control (process) data. The static (failure) data metric of availability (A) for repairable systems is expressed as:

$$A = \frac{E[TBF]_i}{E[TBF]_i + E[TTR]_i} = \frac{MTBF}{MTBF + MTTR}, \tag{1.1}$$

where availability is the division of mathematical expectation of average time between failures $E[TBF]$, denoted as $MTBF$, with the sum of $MTBF$ and expectation $E[TTR]$ of time to repair is denoted as MTTR. The dynamic (process) data metric for operability (O) is expressed as:

$$O = \frac{\int_{t_0}^{t_{end}} \sum_{i=1}^{I} w_i P_i(t) dt}{\int_{t_0}^{t_{end}} \sum_{i=1}^{I} w_i P_{max,i}(t) dt}, \tag{1.2}$$

where I is the number of loads in the system, $P_i(t)$ is the power consumption of load i at time t, $P_{max,i}(t)$ is the maximum required (or demanded) power of load i at time t, and w_i is a mission-specific weighted function of the importance load i.

The general implication is that availability is a measurement tool of a particular system's lifespan performance or maintenance practice performance, while operability is a process measurement based on which one relies on the system's health without failure. The metric operability was first introduced to determine the effectiveness of a power system at the corresponding loads by Cramer [21], [22]:

$$O = \frac{\int_{k=k_1}^{k_{end}} \sum_{i=1}^{I} w_i P_i(t)dt}{\int_{k=k_1}^{k_{end}} \sum_{i=1}^{I} w_i P_{max,i}(t)dt}, \tag{1.3}$$

where *k* represents the discrete-time period in the integer form (from k_0 to k_{end}); furthermore, there are other metrics available that can be derived from operability, such as *dependability* $\overline{D}_s$:

$$\overline{D}_s = E[O] \tag{1.4}$$

which represents a mathematical expectation of operability, and as such minimum system dependability can be used as a metric of the worst-case scenario:

$$\overline{D}_{s,min} = \min[O]. \tag{1.5}$$

Although operability intuitively describes the performance of process health, it does not impose the functionality thresholds from which MDM can be done, both for diagnostic and prognostic purposes. However, some propose different thresholds in the sustainable maintenance domain using energy indicators. For instance, Hoang et al. [23]–[25] define thresholds of energy efficiency using the concepts of Remaining Energy-Efficient Lifetime (REEL) for establishing prognosis or remaining useful life (RUL):

$$REEL(t) = \{(T: EEI(t+T) = EEI_{threshold} | EEI^t < EEI_{threshold}\} \tag{1.6}$$

where REEL represents the evolution of the parameter energy efficiency indicator (*EEI*):

$$EEI = \frac{E}{O} \tag{1.7}$$

where *E* is the total used energy input, and *O* is the useful output in physical units. Logical presupposition reflects the energy consumed to produce a defined output unit. Moreover, further going into analysis, *QREEL,* defined as the probability *q* of the *REEL,* is defined as the time before an object loses its energy efficiency property:

$$QREEL(t,q) = sup\,\{v: P(EEI(t+v) < EEI_{threshold}\} \tag{1.8}$$

where *sup* represents the supremum of the given subset probability *EEI* and is usually perceived as the least upper bound (LUB), with the proposed mathematical expectation of *REEL* as:

$$MREEL(t) = E[REEL(t)]. \tag{1.9}$$

It can be understood that both *QREEL* and *MREEL* are deterministic and, thus, used to evaluate the working system's operational state. It can be inferred that the motivation and rationale for the research include:

(1) The imposition of sustainability on industrial maintenance practice;
(2) Switching the focus from energy-waste indicators to energy-usage indicators;
(3) Limitation of markers for establishing healthy from non-healthy machine state;
(4) Lack of dynamic thresholds for establishing limits for conducting maintenance actions.

1.2 RESEARCH PROBLEM

The production system's functional state in the asset-intensive industry's processes has become a significant issue. The maintenance literature on production systems' proposed functionality thresholds and operability modes face difficulties in modelling deteriorating mechanisms. Most of the authors propose functionality boundaries either as static (rule-based) or moving average, in which failure control limits are defined either empirically or by chance. Hence, the thesis author set to accomplish **functional-productiveness markers** (**FPM**) in light of the argument. To elaborate more closely on the new notion of FPM, the thesis' author will briefly explain the proposed concept of **functional-productiveness control** (**FPC**) [26].

Defining failure by the BSI standard as: "…*termination of the ability of a system to perform required function"* [27] can be considered formulaic since it lacks specific determination of the term ability and functionality. Instead, FPC is proposed to replace the notion of *functionality* with *functional-productiveness* in determining the working conditions (process performance) as binary values, true or false [0, 1]. The *ability* is replaced with the notion of *capability* as "…*system or unit capacity to transfer power"*, which quantifies the ability notion with binary values, true or false [0, 1].

It should suggest that the FPC concept closely resembles process capability in Statistical Process Control (SPC). The difference is that SPC quantifies the capability of a production process, whereas, in the FPC, we are monitoring FPMs that are artificially created for measuring the ratio of machine or component performance. Hence, the SPC explains overall operational performance while FPC presents the machine health index. If we observe the system overall (specific machine) with n subsystems, we can use the Specific Energy Consumption (SEC) indicator to set the thresholds used for classifying healthy from non-healthy systems (Figure 3). For instance, setting the rule-based threshold of at least k out of m required products for a specific input power of P. This can be explained by eq.6, suggesting that after a certain period, the system does not poses the capacity to fulfil the needs of a production process, although the system can be considered operational and functional.

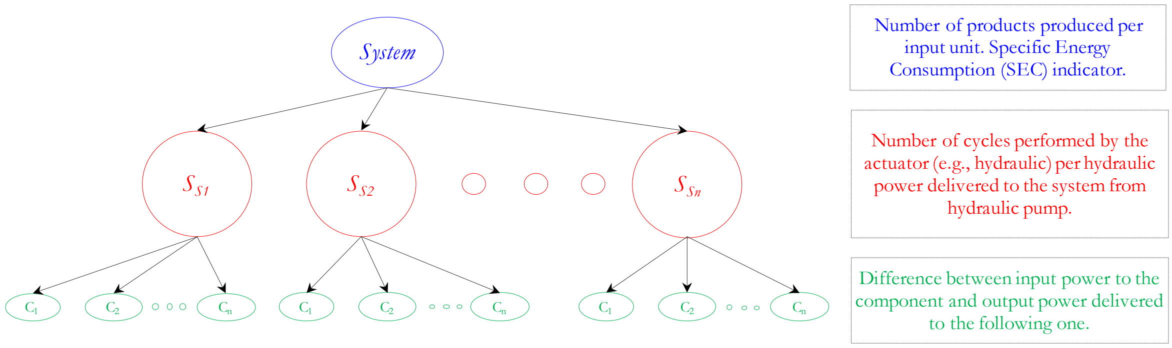


Figure 3. Three-layer system with n sub-systems and n units (components)

Going onto the second layer of observing a specific sub-system (hydraulic), one can infer the same principle without using a product-specific threshold but final actuation device (e.g., cylinder). For instance, if an input hydraulic power reaches a certain threshold where the speed and force of a cylinder drop below a defined range that corresponds to the minimum amount of products required to be produced at a specific interval. At the lowest level of a unit or component, it can be observed that functional-productiveness is the loss between input and output energy, i.e., loss of units' capacity to transfer power after reaching a specific minimum defined threshold.

The literature on the current Predictive Maintenance (PdM) research under the concept of I4.0 utilises modern Big Data analytical tools in assessing failure (diagnosis and prognosis) and optimisation (resources) purposes. However, the literature reports a rule-based approach while upholding the same philosophy of preventing stoppages [28], [29]. Modelling the failure as a static time to an event with an empirical pre-set failure threshold is usually set in the literature as rule-based control limits. These fixed thresholds set either by chance or experience are a major problem in dynamic industrial processes. For instance, some processes may start degrading earlier and maintain some stability over time but cause major problems and consumption of resources since they are working below static thresholds (left in Figure 4). These fixed thresholds do not work well over a longer period. Therefore, re-defining control limits after each specific production batch can cope with such instances since an expectation is that the process will have some degree of degradation over time. Therefore, the thesis author introduces the dynamic signal thresholds (right in Figure 4) abstracted as quasi-faults (QF). This can help differentiate between total failure (TF) thresholds to optimise decision-making and conduct maintenance actions based on dynamic reasoning when a certain QF is surpassed. That way, processes can always be maintained at a "peak" efficiency without stoppages.

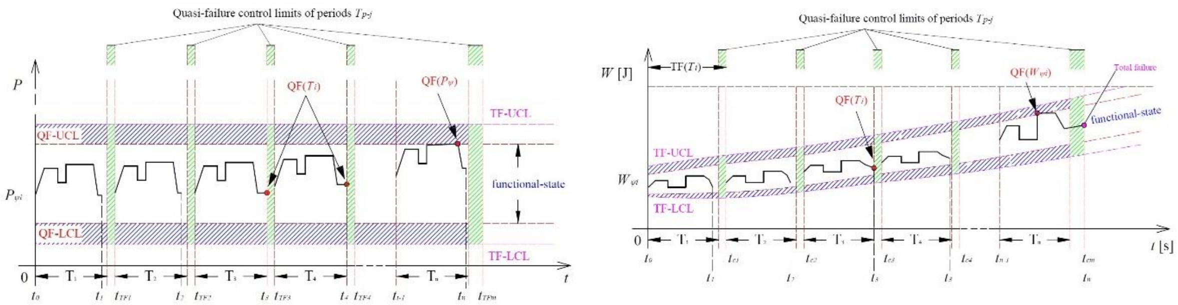


Figure 4. Functional-productiveness control boundaries with quasi-faults (QF)[26] for static thresholds (left) and dynamic (right) thresholds

Under the EBM paradigm, the goal is to allocate markers suitable for re-defining indicators for assessing machine state health. The research problem being addressed in the thesis is the determination of markers important for binary classification (diagnostic) purposes in separating healthy from non-healthy states [0, 1]. At the same time, these markers will be used for the reliability analysis of different scenarios to optimise maintenance decision-making. Therefore, several statistical parameters will be used to assess the system behaviour. For instance, the most commonly used markers of such kind are mean value (μ) and variance (σ^2) or standard deviation (σ), which are used to establish the process behaviour compared with input and output values of different sources. Aside from using the first raw mathematical moment (mean value) and second centralized moment (variance), the author will also include the third and fourth standardised moment (skewness and kurtosis) and other parameters for assessing the power signal behaviour.

1.3 Research Aims and Objectives

The thesis aims to provide a conceptual framework of EBM and the mathematical formulation of functional productiveness to determine quasi-faults (degradation markers) used for classification purposes. For instance, in the Preventive Maintenance (PM) and CBM domain, the system could be considered operational and functional even if it is causing environmental pollution and reduced operational efficiency. In such circumstances, it causes energy to waste on one side, while on the other, it does not produce enough output to be considered liable and held in operation, depending on the quality practice imposed. The system needs to be stopped and subjected to corrective actions before returning to a ***productive state***, consuming time, costs, and energy.

The FPC concept takes predictors for determining (un)functional-productivity – unsafe and polluting conditions, besides energy (over)consumption. The lack of defined control limits for these markers that are not pre-defined is another cause why data scientists fail to determine and understand the flaws and failure mechanisms. To provide a deeper understanding of the impact of the proposed solution, the author set five research objectives.

The first objective is to investigate the current philosophy of maintenance research by investigating scientific projects in the EU on industrial maintenance. The objective aims to understand the maintenance technology researched behind a particular ideology. Moreover, the specifics of the proposed research objective include (1) determining the most common types of maintenance policies/strategies; (2) searching for the presence of energy-oriented maintenance research within the projects funded by the European Commission; (3) and discuss the lack of achievements, objectively, in comparison to other actual research topics. The goal for specifically addressing these projects is easy to access and transparent meta-data of Framework Programmes of R&I projects through The Community Research and Development Information Service (CORDIS) database. Therefore, the author formulates the objective as follows.

RO1. Investigate projects' research results and dissemination activities related to industrial maintenance research within R&I EU projects. Allocate potential projects related to the energy-oriented research within the industrial maintenance domain and provide a general conclusion regarding the currently ongoing research of industrial maintenance for Horizon Europe.

The motivation for this research objective is seen through (1) the lack of advancement of industrial maintenance in I4.0; (2) research agendas imposed by the Green Deal initiative of the European Commission regarding the decarbonisation of industrial assets by the end of 2050; (3) lack of industrial maintenance R&I projects in terms of sustainable maintenance performance indicators (MPIs).

The second objective includes applying a systematic literature review (SLR) of ongoing energy-dedicated maintenance research. The specific sub-objectives include (1) investigation of the current school of thought regarding energy-dedicated maintenance research under various decision-making levels; (2) elaboration and discussion of potential research gaps and limitations of the proposed methodology; (3) development of the EBM conceptual framework subjected to different MDML (Maintenance Decision-Making Level). The second research objective is set as follows.

RO2. Using systematic analysis, investigate the existing energy-dedicated maintenance research related to MDM and the energy aspect. Reflect on the current energy-dedicated maintenance state-of-the-art research and discuss potential limitations within studies.

The need for such a study is noticed with the exponential rise of the papers investigating the influence between maintenance activities and energy consumption. Thus, potential benefits are noticed through increased demands for energy-efficient solutions and imposed regulations on carbon footprint emissions, which could further justify the need for such maintenance transition.

The third objective is to conduct an industrial survey to investigate the current state of the practice regarding the maintenance of industrial hydraulic machines. The driver for FP exemplification on the hydraulic system is because, arguably, they are the highest source of energy dissipation of all control systems and consequently are mostly subjected to energy-preserving studies. Applying different maintenance practices, tasks, and actions significantly influences energy performance. Moreover, due to its intrinsic relationship in modelling the newly proposed failure-triggering mechanism, for instance, fluid degradation that can produce environmental consequences (e.g., leakage) and economic consequences (e.g., failures, energy consumption), it can be easier to articulate the benefits of FP through a practical example. The research will be beneficial and justified in a more practical and industrially-accepted context by extracting operational and conditional data from state-of-the-practice. Therefore the following research objective is proposed as follows.

RO3. Develop and conduct a questionnaire-based survey that includes: (1) the type of machinery applied across industrial sectors – mobile and stationary machines; (2) maintenance policies, programs and activities applied within manufacturing and service companies on all levels of MDM; (3) the technology applied – type of data acquisition and data processing tools and methods; (4) most common types of failures and causes of stoppages/failures; (5) define and determine the environmental and economic indicators applied for reflecting the success of various practices.

This specific objective is not limited by economic and environmental data but is also projected to determine meta-data and variables that influence the system's operational performances, affecting higher energy consumption. Such data is needed because of the stochastic nature of the bottom-line function subjected to human activities, which is currently being subjected to multiple studies in multidisciplinary research. This information can further help isolate the human factor or give a general understanding of the intrinsic relationship between operational and maintenance activities and their overall performance.

Although monitoring energy can help one understand operational efficiency, i.e., system energy performance, the lack of research is related to the difficulties in determining the appropriate functionality of proposed models in the literature that can help trigger maintenance actions and return or adjust the system into the safe operational state. Generally said, the FPMs with FPC are considered discriminators for classifying functional- from the non-functional state. The fourth research objective is to define markers important for establishing the health status of a machine that can be used for diagnostic, prognostic and optimisation purposes.

RO4. Using supervised machine learning algorithms, determine healthy from a non-healthy machine regarding the hydraulic power variable. Upon determining the most appropriate learning algorithm, extract the most important predictors (markers) that can be used to assess the system's functional-productiveness.

The fourth thesis objective is directed at determining a machine learning model from a hypothesis space, in which the FPMs are extracted based on the most appropriate classification algorithm. The markers are then used to gain insight into machine health; consequently, they can be used for diagnostic, prognostic and optimisation purposes. Therefore, the final research objective is set to determine the system's reliability analysis using the proposed markers and boolean operators to optimize machine performance.

RO5. Conduct a reliability analysis with the proposed FPMs and compare it with the available maintenance practice applied. Discuss the potential benefits of implementing FPC with EBM prospects and potential setbacks in implementing the EBM practice.

The final objective is a milestone for transitioning between the traditional static (failure) data maintenance practice and a dynamic (process) data maintenance practice. Hence, the benefits of accepting the concept of functional productiveness are threefold. Firstly, power consumption can provide insight into the machine's health prediction (maintenance diagnostic and prognostics) and operational performance (production performance). Secondly, energy as a maintenance performance indicator (MPI) can serve as quality control of environmental responsibility in energy usage, and it can also be transformed into an ecological CO_2eq indicator. Finally, energy as an MPI can be used to prevent or reduce stoppages, thus, optimising the system by reducing the consumption of resources.

1.4 THESIS STATEMENT(S)

In today's dynamic but sustainable-oriented technological ecosystem scientific basis for cognising what observable facts constitute is merely a relative observation of the present states. Thus, one would constitute that for a hypothesis, and potential theory, to be falsifiable, it must be inert to changes. The underlying reason for engaging in this narrative is the lack of horisontal-type research studies by initially testing the previously "settled" statements and conditional premises that can eventually mature into accepted theories.

Such criticism, primarily, can be easily verified by the lack of meta-analysis studies in industrial maintenance research. Secondarily, with the focus on replicating failure modes, i.e., physics of failure, that is needed for developing Digital Twins (DT) of failures (DTF), how those digital replicates will be tested and verified according to the unknown (environmental) perturbations drags more questions into states and activities leading to a failure. Thus, big data of causality between states before and after the failure and the process within is insufficient. The underlying reason for that is quite evident – the scarce resources and justifiability for conducting such a study will undoubtedly be ever accepted, regardless of the system or process.

Thus, all the research in the maintenance domain focuses on avoiding or preventing the failure, thus prolonging the remaining useful life of the system or optimising maintenance activities to preserve the resources without the ability to observe and collect data on failure mechanisms. Therefore, the research focuses on the degradational mechanisms and markers associated with, i.e., classifying healthy from the non-healthy state by proposing functional productivity for improving decision-making aimed at diagnosing, prognosing and/or optimising production system.

The author of the thesis aims to dissect "settled statements" of industrial maintenance scientific achievements by questioning the actual advancements regarding industrial maintenance in primary sources. As observed by the shift towards sustainability, maintenance indicators now include energy-dedicated and sustainable performance indicators. Therefore, the author of the thesis will challenge the current "state of the maintenance research" by questioning advancements in maintenance through EU research projects. Secondly, allocate energy-dedicated maintenance literature and discuss potential benefits and setbacks in accepting such radical change. Thirdly, the author of the thesis will challenge the hypothesis that contamination is the leading cause of stoppages in the hydraulic system through a state-of-the-practice questionnaire. Finally, an experimental investigation of hydraulic systems will be done by utilising power-consumption monitoring practice.

1.4.1 QUESTIONING SUSTAINABILITY IN MAINTENANCE RESEARCH PROJECTS

Formalising the thesis statement will be conclusive if, and only if, all the argument's premises can be tested. Identifying that the hypothesis is clearly defined and empirically tested avoids ill-defined propositions not subjected to falsifiability. To support the lack of achievement in the sustainable and energy-oriented maintenance domain, the author first challenges the evidence from state-of-the-projects by formalising the first major hypothesis as:

$\mathbf{H_1}$: „Lack of scientific advancements in industrial maintenance domain is seen due to the lack of sustainability features of maintenance projects funded through the EU."

$\mathbf{h^{11}_0}$: "*Industrial maintenance R&I projects dedicate more towards technological advancements than educational and structural repair in industrial maintenance technology.*"

$\mathbf{h^{12}_a}$: "*Industrial maintenance R&I projects dedicate more towards education and structural repairs than on technological advancements in the industrial maintenance domain.*"

h^{13}_0: "*Industrial maintenance EU R&I projects show a statistically significant relationship between educational and structural repair projects and dissemination activities in industrial maintenance technology*."

h^{14}_a: "*Industrial maintenance EU R&I projects do not show a statistically significant relationship between educational and structural repair projects and dissemination activities in industrial maintenance technology*."

The author's intention here is not to set a majestic scope of the thesis impact but rather a specific, well-defined frame for contributing to the topic of sustainable maintenance. Thus, these problems from which the hypothesis is derived reflect an inquiry into resolving dynamic systems' environmental and technical issues. The goal of such a propositional statement is to ensure continuity in the energy-oriented decision-making, of which the focus is set upon a technologically-sustainable manufacturing ecosystem and research projects dedicated to energy-oriented solutions.

1.4.2 CHALLENGING EVIDENCE FROM MAINTENANCE PRACTICE

For testing the prospect of the EBM within the technical, organisational system, the first idea is to choose an appropriate system in which maintenance strategies have already been utilised. Thus, to accept the solution, let us first challenge and verify the conditional premises accepted before conducting an experimental verification. The goal is to validate the acceptability of energy condition monitoring compared to waste energy p-f curve indicators to conduct maintenance actions. Since the domain is a hydraulic control system, the first task is to collect as much evidence regarding the meta-data associated with the oil-hydraulic system.

The reason for conducting such a selective study is that it is widely known that oil-hydraulic systems are low in energy efficiency. So the first task is to find the most common failures appropriate for conducting analysis using instruments for condition monitoring of the p-f curve. At the same time monitoring hydraulic power for conducting diagnostics will be done by monitoring hydraulic power variables – flow and pressure.

It has been an ever-present notion that the main cause of failures across hydraulic control systems, regardless of the application, are contaminants (particle contaminants [30]; air and water [31]; temperature [32]). Therefore, before using contamination as a non-random deteriorating failure measure and associated condition monitoring tools (e.g., Lubricant Condition Monitoring – LCM), the hypothesis will be formulated to challenge the "settled" statement as follows:

H_2: "Particle contamination is the leading cause of failures of hydraulic systems."

h^{21}_0: "*Contamination of hydraulic system, in general, is at least 70% responsible for all failures in the domain of hydraulic control systems*."

h^{22}_a: "*Contamination of hydraulic system, in general, is not 70% responsible for all failures in the domain of hydraulic control systems*."

As presented with the evidence and to challenge the proposed **H_2** under the hypothesis research model, the survey data shows discrepancies in the actual state of failures regarding the root causes of hydraulic systems. However, divided opinions forced the author to validate the proposed hypothesis that at least 70% of failures can be attributed to contamination. That being said, one can conclude that reliability is strongly influenced by the contamination of the fluid leading to premature degradation and failure.

1.4.3 EXPERIMENTAL VALIDATION AND COMPARISON WITH LCM

Finally, from the evidence collected, a specific hydraulic control system of a rubber mixing machine process will be used to test whether LCM can be used as an indication for measuring energy reduction under the specific maintenance strategy applied. If so, then measuring hydraulic power variables (pressure and flow) would be multicollinear and redundant for decision-making since appropriate predictions can be made just by monitoring particle contamination. Therefore, the hypothesis is set as follows:

$\mathbf{H_3}$: "Under the accepted condition monitoring procedure and maintenance practice applied, particle contamination strongly correlates between non-random deteriorating failure and hydraulic power consumption."

The supporting premises to be investigated are as follows.

$\mathbf{h^{31}_0}$: "*There is a relationship between hydraulic power reduction and particle contamination in a hydraulic system.*"

$\mathbf{h^{31}_a}$: "*There is no relationship between hydraulic power reduction and particle contamination in a hydraulic system.*"

The idea of proposing such a hypothesis is to investigate the existence of multicollinearity and question the need for power monitoring if acceptable predictions can be made by monitoring particle contamination using particle counters and elemental analysis.

1.4.4 MACHINE LEARNING HYPOTHESES SPACE

Machine learning algorithms consist of supervised, unsupervised and reinforcement learning algorithms. The experimental validation will be conducted akin to supervised learning algorithms. However, some unsupervised learning algorithms (e.g., PCA) will be used for data exploration and visualisation (e.g., removing outliers and selecting predictors). Since the prediction (inductive reasoning) includes diagnosing healthy from non-healthy, the outputs are given as a binary variable, i.e., true or false [1, 0].

The learning algorithms that are applied consider binary classification problems. Since the goal is to establish markers used for optimisation purposes by reliability modelling, the task considers selecting the most appropriate model (based on classification accuracy) from hypothesis space (H). These markers establish a target function by mapping inputs (x) to outputs (y) with machine learning algorithms (Figure 5). Therefore, target functions are comprised of hypothesis space (multiple models) in which the most accurate target function is the selected model (hypothesis). The outputs for classification models are labelled as healthy – "None" – suggesting no faults or failures and non-health – "Quasi-fault" mode – where anomalies have been noticed and labelled accordingly. The hypothesis set (H) is a space of possible hypotheses (h_i), while hypothesis (h) is a specific candidate model $h(\cdot) = f(\cdot)$ that maps inputs (x) to outputs (y).

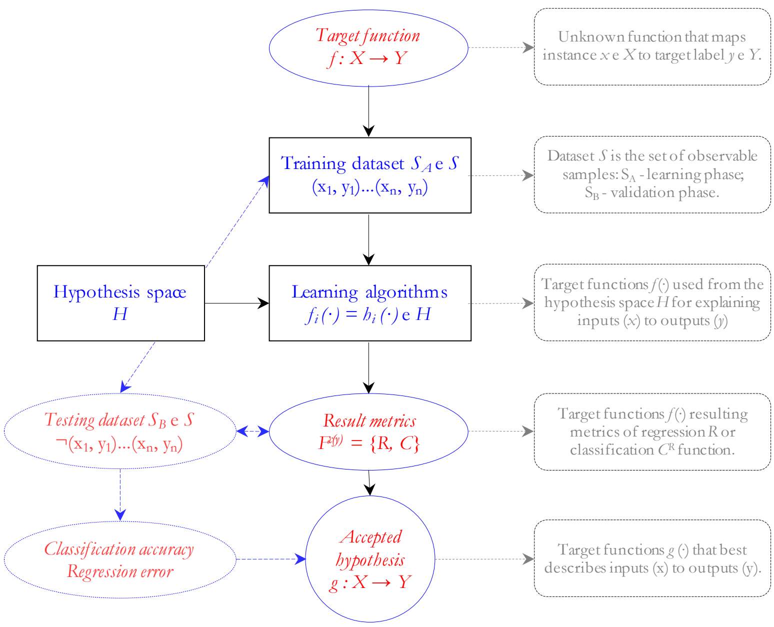


Figure 5. Inductive learning hypothesis testing in machine learning

All possible objects described by the features are called instance space (S). Considering the two-class classification [1, 0] problem, the concept c is a function that explains a specific label feature as $c = f(x|y = 1)$. Therefore, the systems' goal is to learn the concept given the classification outcome. Concept c is considered a subset of instance space for a given $X\{1, 0\}$. Finding the concept c, we determine the hypothesis (h), which is a function that approximates $f(\cdot)$ given label (y_1 or y_0) and imposed language bias (constraint and preference). If we consider an example of determining all possible hypotheses space of binary feature space $\{x_1, x_2 \ldots x_n\}$ the possible instances are $2^{n,}$ and possible boolean functions are then $2^{2^{\wedge}n}$. Given such hypothesis space, it is impossible to examine all possible hypotheses individually to select the best hypothesis. For such reasoning, we impose restrictions and preferences. The amount of hypotheses h_i is restricted by the imposed language bias. The type of restriction bias is ML algorithm – linear function, polynomial function, logistic function, etc. The preference bias includes considering the proposed function but a lower degree function, e.g., lower degree polynomial.

Setting an input (with learning data–training) $S_A \subseteq S$ and output as a hypothesis $h \in H$. To put restrictions on hypotheses space, we select the hypotheses language. The restriction bias is set with the following machine learning candidate models h_i:

(1) Gaussian Naïve Bayes (GNB) classification algorithm;
(2) Artificial Neural Network (ANN) classification algorithm with one hidden layer;
(3) Logistic regression (LR) classification algorithm;
(4) Classification and Regression (CART) Decision Tree classification algorithm;
(5) k-Nearest Neighbour (kNN) classification algorithm.

Both parametric and non-parametric as well as linear and non-linear learning algorithms are used. The preference of the learning outcome is that hypothesis (model) will be chosen for extracting predictors based on the performance metrics of given unseen (testing) data. The performance metrics for classification include a considerable amount of calculations (e.g., Accuracy, Precision, F1, Recall); however, for the sake of simplicity, we will use the *Accuracy* metric of the classification matrix given as:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}, \tag{1.10}$$

where TP represents true positive predicted; TN represents true negatives predicted; FP predicts false positives; FN predicts false-negative classes.

Considering the information provided, the final thesis statement is set as follows.

"Considering an instance space S_A generated by the unknown function $y = f(x)$, using functional-productiveness markers ($FP_m^{(i)}$), it is possible to approximate the true function $f(\cdot)$ with a given candidate model $h(\cdot) \in H$ that maps inputs (x_i) to outputs (y_i) given unseen data S_B."

Given the thesis statement, the following restrictions and preferences are imposed:

- The instance space S is considered a dataset of all possible instances and attributes, where S_A is the learning (instance) space, a randomly generated sample consistent with S ($S_A \in S$), such that $S_A \neg S_B$, where S_B is the unseen data of the learning algorithm.
- y_i, where class $i \in \mathbb{R}^d$ $d=\{1\ldots n\}$, such that $d \geq 2$ for the classification problem.
- Functional-productiveness markers $FP_m^{(i)}$ are probability parameters extrapolated from an observed system' (i) power data (elaborated in 10.1), such that power data is a measure of hydraulic power in the thesis experiment.
- Functional-productiveness markers $FP_m^{(i)}$ are statistically significant if the p $value < 0.05$ criterion is satisfied.

1.5 OUTLINE AND KEY REMARKS OF THE THESIS

This thesis consists of four chapters with sections within each chapter. For practicality, the reader is kindly asked to follow up on Table 1, where descriptions of limitations and opportunities are also given. By providing descriptions of limitations and opportunities, the goal is to identify potential research gaps, opportunities for research continuity and limitation of the provided information.

The **first chapter** explains the theoretical foundation of existing empirical evidence regarding maintenance as a scientific discipline. In addition, it explains the framework in which industrial maintenance finds itself in the technological "4th Wave", emphasising the lack of achievements and latching on to the sustainability aspect. The fourth part of the first section provides a statement with supporting premises to be challenged for the final thesis statement to be valid, after which an outline is given. The second section explains protocols for extracting and dissecting evidence from various sources: (1) EU projects database; (2) scientific literature databases; (3) reports and empirical evidence from reports and databases established in practical working conditions. The last section provides key takeaways from the introduction and elaborates on the protocol and evidence applicability important for the thesis outcome.

The **second chapter** comprises three pillars of evidence to justify the conceptual framework of the Energy-Based Maintenance (EBM) paradigm as a new strategic manifesto for approaching diagnostic, prognostic and decision-making activities within maintenance decision-making layers. The underlying reason for evidence synthesis from these sources of evidence, i.e., practice, projects and literature, served as an apparatus to justify the arguments behind the concept of needing an EBM research framework. The fourth section provides research results of collected evidence from research projects in the form of meta-data. The fifth section provides empirical evidence from collected primary research studies regarding energy-dedicated maintenance contributions of each layer of decision-making. The last section provides questionnaire-based survey results of hydraulic systems' maintenance practice and results of implemented practice. Aside from practical results, the meta-data of collected evidence is used later for selecting an appropriate experimental system.

The **third chapter** utilises machine learning algorithms for selecting appropriate candidate models given extrapolated parameters abstracted as functional-productiveness markers. These are evaluated through their variable importance (VIP) for contributing to the model classification accuracy. After testing all candidate models, the model with the highest classification accuracy is chosen, and their associated predictors are used for reliability modelling. The reliability modelling is used for optimisation purposes where time to an event is chosen on boolean operators of functional-productiveness markers. The seventh section elaborates on setting and preparing the experiment, data collecting and filtering. The eighth section provides data extraction and pre-processing methodology for machine learning training and testing. The ninth section elaborates on each ML model utilised, parameters and results achieved through the accuracy of classification matrices.

The **fourth chapter** consists of three sections: The 10th section of the third chapter includes reliability modelling and optimisation, suggesting improving a system's health through different maintenance actions. The 11th section discusses empirical evidence and results associated with data collected through the doctoral thesis; the 12th section provides concluding remarks as an overview of the thesis outcome, contributions to the literature and limitations of the study with a brief overview of the future research work, main limitations of the proposed solutions and research interest objectives for the post-doctoral research.

Table 1. Outline and organisation the thesis

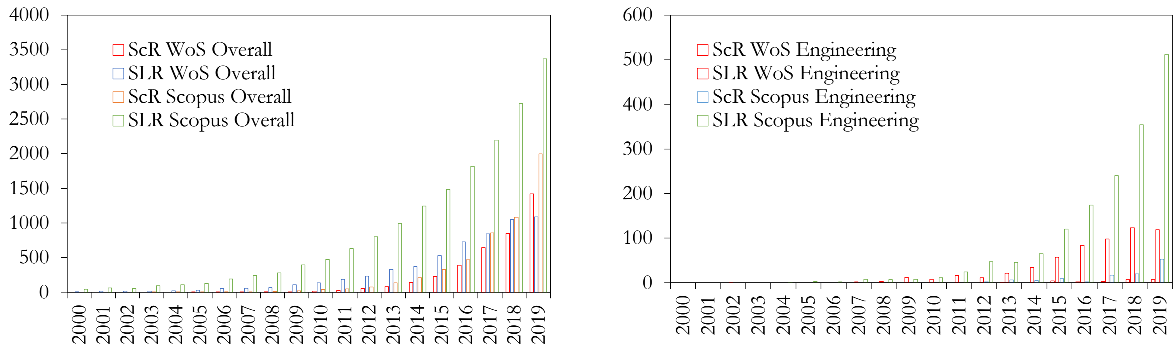
#	Section	Highlights	Oportunities	Limitations
Chapter I	1. Introduction	• Identifying setbacks of industrial maintenance advancements in the technological "4th Wave" era. • Elaboration on the need to transfer from static (failure) to dynamic (process) data. • Proposition and statement on the functional-productiveness markers.	Contribution to the evidence collection. Sustainability in the maintenance sphere for data processing. Functionality markers.	Lack of meta-analysis studies in industrial maintenance. Insufficient information regarding functional productivity.
	2. Protocol	• Research protocol description for synthesising projects', literature', and practical evidence. • In-detail description of each protocol for extracting evidence and data processing.	Effective in making conclusive arguments. Better research insight.	It takes a long time for evidence collection and processing (updating).
Chapter II	3. Projects	• Representation of results – collected and processed evidence from research EU projects.	New sources of empirical evidence.	Lack of meta-data from CORDIS base.
	4. Literature	• Representation of results – collected and processed evidence from energy-dedicated literature.	Opening the chapter on sustainable maintenance.	Insufficient and scarce original evidence.
	5. Practice	• Representation of results – collected and processed evidence from failures on hydraulic systems.	Rejecting the hypothesis of contaminant-induced failures.	Lack of original databases from respondents.
Chapter III	6. Experiment setup	• Explanation of experimental set-up – given the acquired information from the practice.	Data processing with implement maint. policy.	"In vivo" machine process.
	7. Experiment result	• Working conditions, characteristics, fluid sampling, APC, flow and pressure, SCADA.	Data correlation with power parameters.	Data preparation. Big data analytics.
	8. Data preparation	• Explanation of pre-processing and filtering of data. Setting functional-productivity markers.	Data exploration via unsupervised learning models.	Missing data for association rules.
	9. ML models	• Explanation of individual candidate models and applicability of markers for supervised learning with classification results..	Setting parameters for improving accuracy.	Lack of algorithms (e.g., random forest).
Chapter IV	10. Reliability analysis	• Optimisation of maintenance practice through reliability theory.	Improving maintenance decision-making.	Lack of empirical evidence.
	11. Discussion	• Explanatory remarks regarding the current state of energy-dedicated literature through projects, practice, literature and experiment.	Differentiating between layers of CM applicability.	Lack of energy-dedicated research studies.
	12. Conclusion	• General thesis overview. Contributions to the literature. Implications of the proposed idea.	New research directions with unsupervised learning.	Lack of data for unsupervised learning (AR).

2 RESEARCH PROTOCOLS AND METHODS

A systematic research protocol for every pillar is proposed to mitigate vagueness and systematic errors in extracting valuable information by respecting scientific ethics, thus distinguishing quality from quantity. To understand the other's ability to make conclusions and outcomes with sophisticated exactitude, one must replicate the process of synthesising evidence and reproduce the results provided by the priori. Following Karl Popper's school of thought further motivated the author of the thesis to propose explicit research protocols for respecting transparency and reproducibility. These protocols for extracting relevant data rely upon Evidence-Based Practice (EBP) [33]. Although protocols are mostly utilised in medical practice, knowledge transfer is ever-present in social, natural and engineering sciences. The EBP or EBA (Evidence-Based Approach) [34] is becoming popular through the use of systematic reporting of literature, usually under the notion of Systematic Literature Review (SLR) [35]. Each protocol for extracting relevant evidence will be elaborated in detail in the following sub-sections.

2.1 RESEARCH PROTOCOL FOR EXTRACTING EVIDENCE

Systematic reviews have been celebrated in the last couple of years (Figure 6) due to their base principles in mitigating bias – respecting transparency and replicability. Although, by the thesis author's experience, while some also argue for [34], the SLRs paper seems to be privileged more narratological than critical approach, especially in the industrial maintenance domain [36], [37]. Namely, the SLR must exclusively rely on the primary-source studies [38] respecting the target of the research question, while the ScR (Scoping Review) targets broader research questions [39], [40] by which data includes primary and secondary sources. Unlike the SLR, where the goal is to answer the proposed question utilising only primary publication sources with a horisontal question, the goal of the ScR is to answer a much broader, thus vertical, research question.



(a) (b)

Figure 6. SLR and ScR reviews overall (a) and engineering (b) by WoS and Scopus

The lack of appropriate methodology and differing interpretations of evidence does not allow critical appraisal of evidence, thus lacking falsifiability criteria. Without respecting the replicability and reproducibility of the results, we, as research peers, cannot achieve theory advance. Recently, a 2016 poll reported in the journal *Nature* suggests that over 70% of the 1500 respondents were unable or failed to reproduce another scientist's experimental results, and even more worrying is that 50% of scientists failed to reproduce their own [41]. Studies in industrial maintenance also fail to provide transparent methodology or protocol for extracting relevant evidence. For instance, a systematic review study [42] researching the benefits of LCM for MDM fails to show the methodology utilised; hence the study cannot be replicated. A similar study [43] excluded at least ten papers regarding the sustainability aspect of MDM.

Consequently, such research reports appear to be more elusive than exact due to latent research methods. In that case, the author provides a more reliable and well-established protocol with exegesis of previous methods given by various authors within the same research field. These considerations forced the author to place a loop on evidence synthesis by providing a transparent and replicable research protocol for extracting relevant evidence from various sources.

2.2 RESEARCH PROTOCOL FOR STATE-OF-THE-PROJECTS [58]

Theoretically speaking, the scientific commuity expects that industrial projects provide sound ways for altering maintenance; however, statistics show it is not straightforward [44]. It is questionable whether direction of R&I are focusing on technological development or maintenance repair. Since in the second case the benefits are quite dubious considering technological and economic growth. More worrying is the fact that, in some instances, multimillion-maintenance-related projects after evaluation show a lack of contribution and impact [45]. The research work on maintenance, on the other hand, shows the proliferation of narrative, critical, and systematic reviews [13], [37], [46], [47], emphasising saturation and the lack of maintenance progress in sustainable manufacturing [48]. On the other hand, proposing novel approaches with defamiliarisating narratives by reinventing existing concepts seems to resemble a strawman fallacy. Some argue [24] that overlooking sustainability indicators [49], such as energy efficiency or carbon footprint in the decision-making process, as in the case of [43], are seen as setbacks for maintenance evolution.

2.2.1 SETTING THE RESEARCH QUESTIONS

Although existing maintenance policies help one understand their principles, none of them specifies which strategies should be utilised in the specific industrial domain. Hence, the author sets two research questions to respond to the first research objective.

RQ1. Within the research EU Framework Programmes (FP), which dedicates to industrial maintenance research, which maintenance strategies or programs stand out the most for a particular industrial application?

The proposed question distinguishes the number of research projects quantitatively within a specific industrial domain. The aim is twofold: to investigate the presence of energy-oriented maintenance research projects and maintenance research interest within EU programmes. Furthermore, academics and practitioners would expect that R&I projects provide novelty in terms of altering maintenance fundamentals or perhaps Intellectual Property (e.g., patent, design, or know-how). However, R&I maintenance projects seem to focus more on the education aspect and structural repairs than on technological advancement. Therefore, the second question is proposed.

RQ2. What are the overall research outcomes and dissemination activities of R&I maintenance projects funded by the EU, and how are they portraying maintenance development?

The goal of proposing such a question is threefold: (1) to investigate the correlation between funds invested into R&I projects with expected scientific and technological deliverables; (2) to highlight the uneven scientific and technological contribution of maintenance EU projects; and (3) to discuss the lack of achievement of industrial maintenance technology within EU maintenance-related projects.

2.2.2 SETTING ELIGIBILITY CRITERIA(S) [58]

A corpus of projects realised between 2000 and 2019 using Community Research and Development Information Service – CORDIS (https://cordis.europa.eu/) is analysed. The CORDIS repository consists of all EU-funded research projects and their results [50]. The underlying reason for choosing CORDIS is because the network has transparent data of all projects funded in the EU under the Framework Programmes. Moreover, the Green Deal initiative also served as an apparatus to illustrate why such legislation can be used as a research directionfinder. The Green Deal initiative is also one of the motivational aspects where the primary interest is to reduce carbon emissions on a continental level, including sustainability in everyday industrial decision-making. Therefore, including the sustainability element, such as energy, cannot be overseen because of energy waste and carbon emission influence in MDM.

The first step of systematically reporting and extracting evidence is setting the eligibility criteria (Table 2), including inclusion and exclusion. Inclusion criteria encompass main features of interest, while exclusion criteria serve as a tool to exclude non- and loosely-related projects regarding proposed RQ1 and RQ2. The goal is to search only for the projects dedicated to industrial maintenance research and exclude others. The time frame is based on the framework programmes realised from FP5 to FP8 (Horizon Europe).

Table 2. Description of inclusion and exclusion (I/E) criteria

I/E criteria	Sub-criteria	Description of criteria
Inclusion criteria	Projects funded by EU/EC (PEC)	Projects included for evaluation can only be from the European Commission's projects.
	Repository of Projects (RoP)	Results are from the repository of the CORDIS database (https://cordis.europa.eu/).
	Framework Programme Projects (FPP)	Framework Programmes for Research and Technological Development (FP5-FP7) and Research and Innovation FP8 (H2020) projects.
	Time Frame (TF)	The time frame is set from 01.01.2000 to 01.01.2020.
Exclusion criteria	Non-Related (NR)	NR1: Projects not dealing with industrial maintenance (e.g., medicine, biology) are excluded. NR2: Projects that appear after the search due to keyword bias; however, they do not address research on industrial maintenance are excluded.
	Loosely-Related (LR)	LR1: Projects that deal with the services of softwares, programs, or algorithms but not with industrial maintenance practice. LR2: Projects dealing with social challenges, ergonomics, business, and other non-specific industrial maintenance projects.

After setting the eligibility criteria and extracting keywords and syntaxes from research questions, the following step defines strings for searching projects related to the proposed RQs while respecting eligibility (I/E) criteria.

2.2.3 Search strings and search protocol [58]

Given the proposed RQs, search strings are modelled and depicted in Table 3. The search strings should encompass the most common maintenance strategies and programs applied in the industrial maintenance research domain. After searching the most common strings in industrial maintenance research, an additional snowballing search is used for keywords with asterisks (*) to find related projects that the standard search may omit eventually. The project research and analysis follow two phases (Figure 7). Through screening of projects' factsheets collection of relevant data considering inclusion (PEC, RoP, TF, FPP) and exclusion (NR1, NR2) criteria is performed. Rest of the projects are subjected to an exhaustive review. Exclusion LR1 and LR2 criteria exclude projects not related to maintenance practice. According to CORDIS search guidelines, a snowballing search is conducted using various search strings. After selecting closely related projects, an in-detail description of projects' meta-data, outcomes, dissemination activities, and resources are presented and elaborated.

Table 3. Search results of the projects using defined search strings [58]

Search action	Description of search strings	No. projects
Keywords	*"predictive maintenance"*	101
	"structural health monitoring"	109
	"proactive maintenance"	11
	"condition-based maintenance"	34
	"prognostics and health management"	4
Sub-total		259
Inclusion criteria		-68
Exclusion NR		-26
Exclusion LR		-21
Duplicates		-14
Snowballing	*contenttype='project' AND ('WITHIN' AND 'TITLE' AND ('mainten$' OR 'failur$' OR 'condition'' AND ''monitoring' OR 'diagnosis' OR 'prognosis'))*	+45
Total Projects		175

Besides CORDIS, *OpenAIRE*, *Google Scholar*, and websites are additionally covered for extracting essential deliverables (e.g., publications, patents). Two types of information are collected: meta-data and project report data. Projects' meta-data consists of (1) title and acronym, (2) coordinator and country, (3) link to meta-data, (4) project FP program, (5) year (start to finish), (6) institutions (coordinator and partners), and (7) industrial sector. Project report data consists of (1) types of publications, and research outcomes, (2) overall project budget and EU funds, and (3) type of maintenance policy or program addressed.

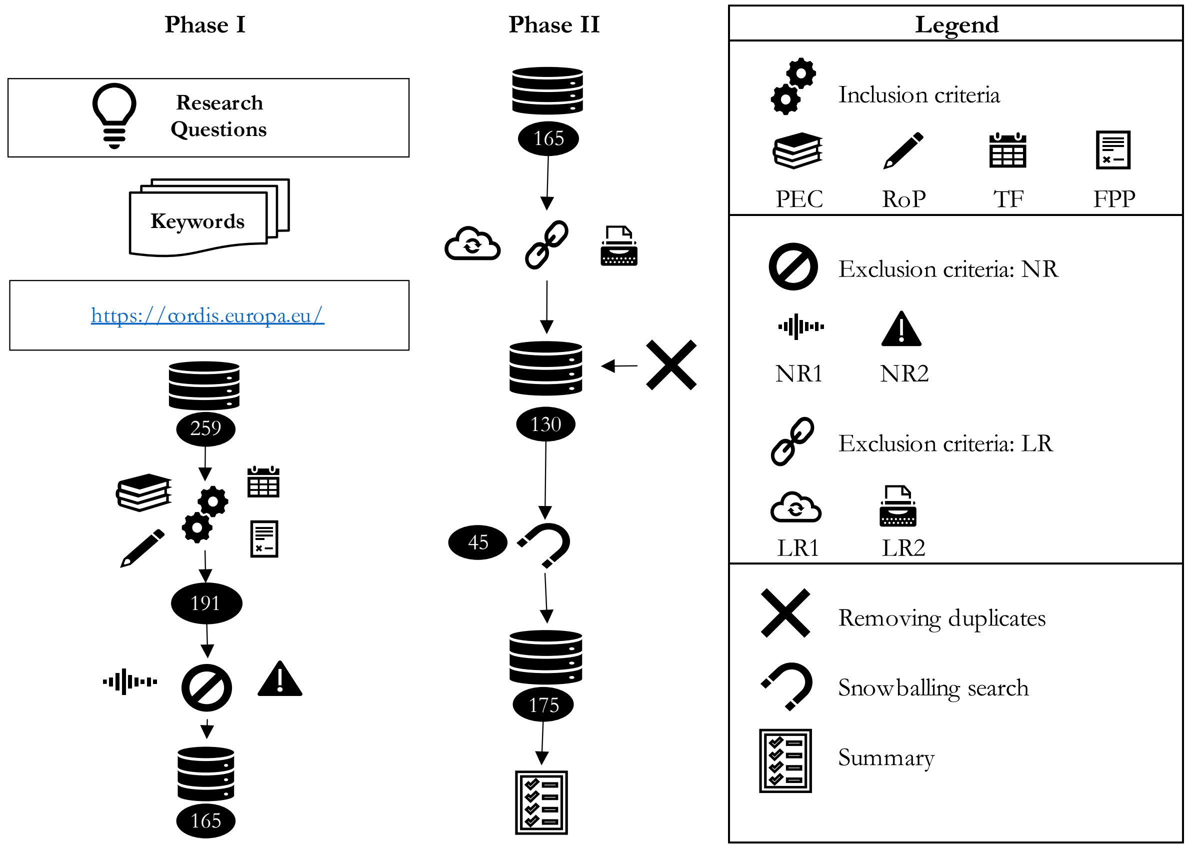


Figure 7. The protocol for extracting projects in the corpus of evidence [58]

2.3 RESEARCH PROTOCOL FOR STATE-OF-THE-PRACTICE

2.3.1 SETTING THE RESEARCH QUESTIONS

The first building block for achieving the third objective is to extract all the relevant evidence concerning industrial maintenance typologies and meta-data applied to hydraulic control companies. The survey investigating state-of-the-practice hydraulic system properties and maintenance is shaped akin to EBA, and therefore, the data collected is done through a survey. The third research question establishes the characteristics of interest for selecting an appropriate system.

RQ3: What are the most common characteristics of the hydraulic systems applied in an industrial environment, including machine, fluid and working characteristics?

The question should extract all the relevant meta-data regarding the operational and environmental working conditions interested in conducting failure analysis. The question's goal is to reflect the current state of the practice of companies applying maintenance on hydraulic control systems. The following question encompasses the maintenance characteristics that include policies, programs and activities applied in a specific company and on specific machines. Therefore, the fourth research question is defined as:

RQ4: Within existing maintenance policies and programs of hydraulic machinery applied by industrial companies, what are the most common activities and tools applied for improving maintenance performance, i.e. failures of hydraulic machines?

The question implicitly should answer several issues: (1) What are mostly applied maintenance practices?; (2) What the most common oil analysis program applied is?; (3) what are the most common sensors and instruments used for MDM? The questions should detect variables that affect the machinery deterioration process, i.e., indicators (e.g. oil waste, failure types, root causes).

RQ5: What are the overall results of various maintenance policies and programs applied in general maintenance performance indicators, including environmental consequences?

The final question's goal is to reflect the consequences of applying different maintenance policies regarding maintenance technical and sustainability indicators and draw conclusions on the importance of each variable and maintenance activities for improving those indicators.

2.3.2 SETTING THE SURVEY TARGET

A questionnaire-based survey is used as one of the data-driven research instruments to validate the evidence collected and highlight the importance of the need for such a survey. The survey is conducted in three phases (Figure 8): (1) design and development; (2) simulation and sensitivity analysis; (3) survey realisation – data collection and processing. The questionnaire is designed to encompass bottom-, mid- and upper-level maintenance hierarchy while targeting:

A. Operational aspect: company size; asset management resources; type of technical systems – industrial, mobile, marine, aerospace; the system's pressure; technical parameters – working conditions, forces, pressures, and flow.

B. Maintenance aspect: strategy and action plan; monitoring programs; instruments and sensors applied; activities employed; mathematical and statistical tools for processing and maintenance decision-making.

C. Performance aspect: type of failures; root causes of failure; failures of particular components; the mean time between failures (MTBF); filter replacement period; oil consumption; and oil refilling.

The pilot version of the survey contained 80 questions with the same targets and audience to investigate. However, after only a 3% response rate in the first couple of months, the survey was shortened to 20 most important questions (including subquestions) regarding the maintenance practice of hydraulic systems while maintaining the proposed research objective. The design phase is realised through discussions with the research scientists and industrialists. The survey is designed to be transparent, broad (including various regions), and understandable (reworked with other experts in the field and tested to mitigate bias). Hence, the survey was disseminated to several other researchers after design and in various geographical regions without prior cooperation with the researcher.

2.3.3 IMPROVEMENT OF THE SURVEY

The survey design's start date was March 2019 and lasted until June 2019. During that period survey was redesigned and improved according to suggestions from other researchers in the field. The survey was sent to the industry and redesigned according to environmental requirements for fulfilling such a document.

The survey is shaped to provide mostly numerical quantitative data for descriptive statistics and better insight into the real problems and facets of hydraulic machines' maintenance practice in various sectors. In other words, the primary aim of the survey is to reflect the current state of the practice regarding operation & maintenance (O&M) activities of hydraulic systems.

The second aim is to extract essential information regarding the real-working conditions from which the experimental machine, i.e., the "in vivo" system, will be used for experimental validation using machine learning models and proposed functional-productiveness markers.

The third aim is to use meta-data from practical conditions, maintenance activities and associated actions to optimise maintenance activities via reliability modelling and analysis and discuss the contribution to the EBM practice.

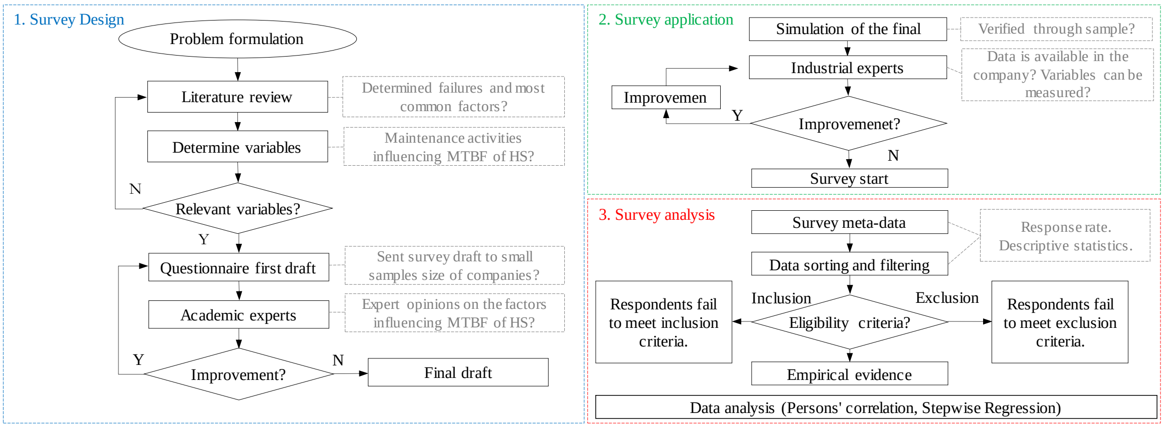


Figure 8. Survey framework draft of hydraulic system maintenance

2.3.4 SURVEY REALISATION

The first draft of the survey was sent to the two industrial maintenance scientists on hydraulic system maintenance research for review. The survey is also sent to three companies to review the survey structure for clearness and transparency. The aim is to acquire knowledge regarding the survey structure and suggest whether it was explained in detail for surveying within an industrial environment. The survey was reduced from 80 to 30 questions after experts' suggestions. After the first test period, the response rate was less than 5%, after which the survey was again shortened and redesigned such that the final version of the survey contained 21 essential questions split to target the aspects proposed (Appendix 1).

Table 4. Inclusion and exclusion criteria for survey validity

Criteria	Explanation	# Accepted
Inclusion criteria	A company must have hydraulic control systems within the proposed machine's working mechanism.	-2
	A company must have a maintenance department and personnel or outsource a company with a maintenance contract.	-6
	A company must have information regarding the machines and associated data.	-2
Exclusion criteria	The company is unwilling to share **all** the data under its policy agreement for research purposes.	-2
	The company did not complete the whole survey even after contacting again.	-5
	The data shows a discrepancy in the survey results while conducting the survey data's reliability and validity.	-4
	A company does not have a precisely defined maintenance policy.	-7
	SUM	72

The test runs sending of the survey contained 297 companies, including firms that use hydraulic power static machines (e.g. presses, extrusion lines), mobile machines (e.g. mining companies), maritime (e.g. ship hydraulics) and aero (e.g. aeroplanes and helicopters). The region selected for the survey was the Balkan Peninsula. However, after the survey test, no response was received other than countries: Serbia, Montenegro, Bosnia & Herzegovina and Croatia. After eliminating the countries with no response, even after contacting, the research area was shorted and left with 235 companies. The survey was accomplished with a 42.55% response rate. The author provided an inclusion and exclusion table to eliminate all those surveys that did not pass the analysis's basic requirements to reduce the partiality and bias of results.

2.4 RESEARCH PROTOCOL FOR STATE-OF-THE-LITERATURE [58]

2.4.1 SETTING THE RESEARCH QUESTIONS

Aligning with the Horizon Europe "Green Deal" target [51], the energy feature is now encompassed with maintenance since research evidence suggests positive effect on decision-making process [52]–[55] and indicator for sustainability issues [23], [25], [56]. The general notion is that literature on energy saving issues considers production-operational progress [57], which provoked some maintenance scholars to include energy in maintenance decisions and policy-making. Therefore, the question for surveying the existing literature is set as follows:

RQ6. What existing concepts and propositions in energy-dedicated maintenance research will contribute to industrial maintenance's technological progress in Horizon Europe?

The interest here is to overview maintenance concepts and programs, investigate the benefits of a new research agenda, discuss potential gaps, and investigate sustainability factors as a primary construct of maintenance advancement. As discussed earlier, the main setback of maintenance time series analysis and prognostics is related to static and rule-based failure-functionality thresholds, resembling static and planned maintenance activities, instead of real-time activities aimed at hazard analysis of potential stoppages. Therefore, the final research question includes reviewing and critically evaluating existing models within the energy-oriented maintenance research dedicated to transforming from rule-based to dynamic-based functionality and failure thresholds. The final research question is defined in the following.

RQ7. What are statistical and mathematical models within the energy-based maintenance paradigm used for different levels of maintenance decision-making, and what are a pre-defined failure or functionality thresholds for diagnostic purposes?

The primary aim of the question is to review existing models and discuss their inability to be used as dynamic boundaries and investigate the thresholds (fault) boundaries used at different layers of MDM, including process (control) data.

Table 5. Search strings for retrieval of publications [58]

Feature	Description of strings	SD	Scopus	WoS	Sum
Keywords	*"energy efficiency" AND "condition-based maintenance" AND "energy consumption"*	121	124	9	254
	"energy efficiency" AND "predictive maintenance" AND "energy consumption"	228	102	7	337
	"Energy-based maintenance" OR "maintenance based on energy" OR "energy-oriented maintenance"	14	18	4	36
Sub-total					627
Duplicates					-185
Inclusion crit.					-398
Exclusion NR					-13
Exclusion LR					-8
Exclusion PR					-3
N/A papers					-1
Snowballing (SB)					+8
CR papers					27

2.4.2 DEFINING ELIGIBILITY CRITERIA [58]

Setting eligibility (I/E) criteria for extracting relevant information is done in two phases (Table 6). Firstly, basic technical criteria for establishing the focus of extracting studies are defined. Secondly, to narrow the search, three subcriteria are set to find only the studies that correspond to the RQ providing an explicit relationship between energy and maintenance, either used as a parameter for diagnostic, prognostic or optimisation purposes.

Table 6. Eligibility (I/E) criteria for evidence extraction from the publications [58]

I/E criteria	Sub-criteria	Description of criteria
Inclusion criteria	Papers must be full text (FT)	Publications such as posters, abstracts, and editorials, will not be included.
	Papers must be in English (ENG)	A research paper must be written in the English language to be included.
	Original peer-review study (OPS)	Studies are not included if they are not peer-review and original (primary) literature sources.
	Time Frame (TF)	The time frame is set from 01.01.2011to 31.12.2020.
Exclusion criteria	Non-Related (NR)	NR: Articles that appear but are not original research studies (e.g., materials, procedures, forewords).
	Loosely-Related (LR)	LR: Research does not explicitly describe the relationship between maintenance influence on energy or using energy as an indicator for MDM.
	Partially-Related (PR)	PR: Research is focused on monitoring the energy aspect; however, it only provides statistical energy values with a poor relationship between maintenance and energy.
Eligible	Closely-Related (CR)	CR: Studies corresponding to the RQ provide an explicit relationship between maintenance activities/actions and energy consumption.

Following the search strategy, the PRISMA protocol (Figure 9) illustrates systematic reporting and extraction of evidence. For each included paper in the analysis, three types of information are collected and entered: article meta-data, study application and policy, and content-based evidence.

Information regarding the meta-data of collected articles consists of (1) title of the article, (2) first author, (3) year of publication, (4) institution, (5) category of publication (conference or journal article) and (6) database. Application and policy within a research article consist of evidence regarding (1) industrial sector or application, (2) efforts within a particular maintenance policy, and (3) maintenance concepts within those policies. Finally, content-based evidence includes (1) research methods or concepts used, (2) sustainability constraints, (3) failure limits or thresholds, and (4) maintenance aspects addressed (diagnosis or prognosis), if applicable.

2.4.3 PRISMA PROTOCOL FOR SURVEYING THE LITERATURE [58]

After finishing the state-of-the-projects review in the EU, a literature survey is conducted following the PRISMA framework [59] guidelines. Based on the research questions (RQ6-7), keywords and Boolean operators were modelled to form search strings (Table 5). Encompassing search strings concerning eligibility criteria (Table 6) showed that 19 articles were eligible for review. Besides, after screening references within these papers, seven more papers were found to answer the proposed RQ. In total, 27 papers were suitable for critical appraisal of evidence.

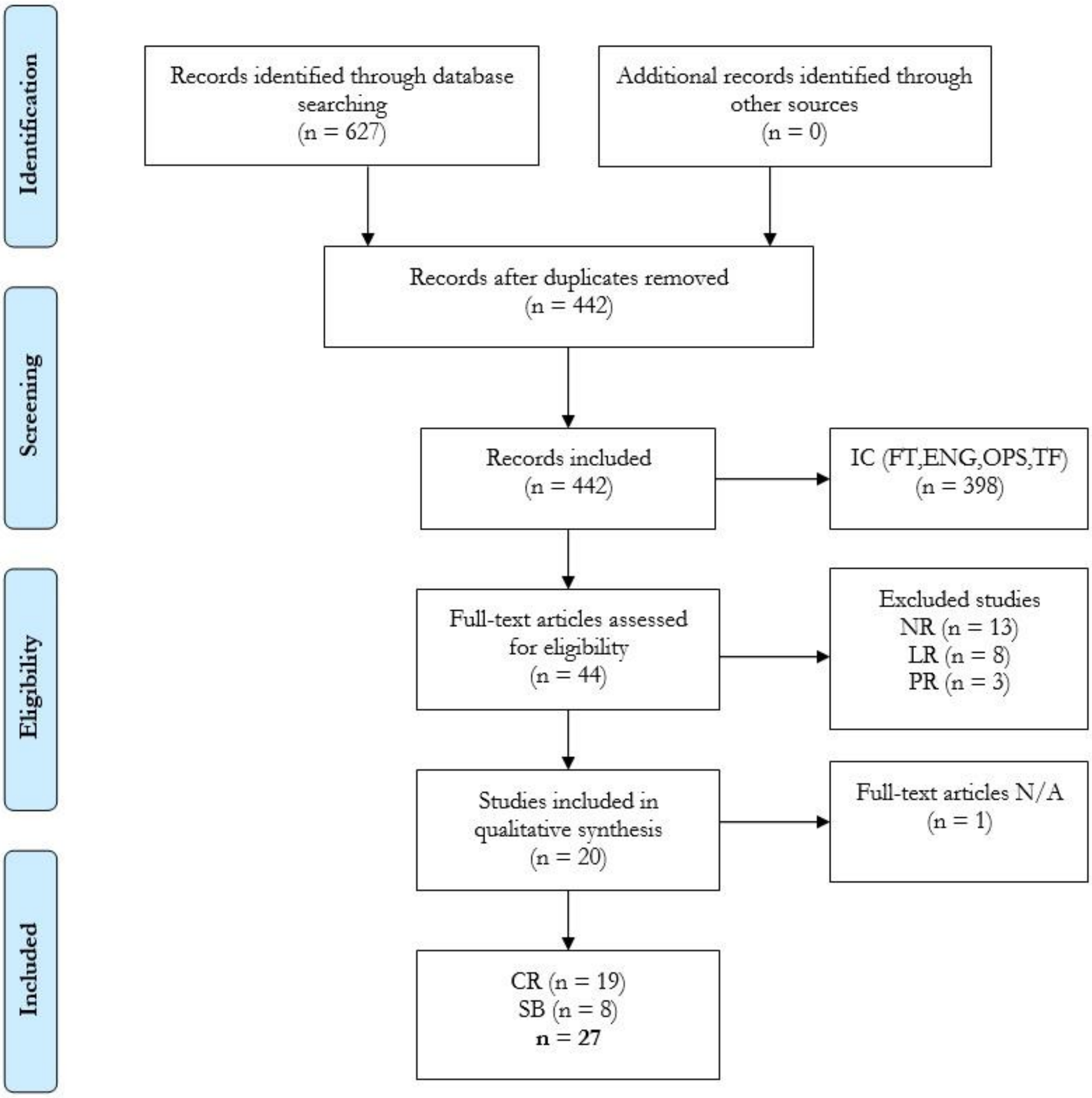


Figure 9. PRISMA framework for retrieving research articles [58]

Chapter II

"Rather than love, than money, than fame…give me truth."
Henry David Thoreau

3 STATE-OF-THE-PROJECTS RESEARCH RESULTS

Like many research projects and scientists associated, which presumably are justifiably warranted with funds for the research that, again, presumably resonates with the zeitgeist, the scientific topics under those projects provide a perfect illustration of a maintenance manifesto with their impact on resolving global (or at least EU) issues. Research frontiers of different maintenance facets seem to be reaching their steep slope towards horizontal-type studies – suggesting saturation in the industrial maintenance field. From a scientific perspective, current maintenance scientists provide un-sound reasoning, both in primary and secondary source studies, claiming that maintenance as science has experienced transformation along with Industry 4.0. These arguments, however, only show slight advancements and re-invention of existing concepts while latching onto catchphrases of the I4.0 lingo. To avoid synthetic buzzwords of "maintenance 4.0" and distorted arguments of maintenance advancements led the author of the thesis to use CORDIS project's data as an apparatus to rationalise and provide a clearer understanding of the obsolete maintenance indoctrination.

3.1 MAINTENANCE PRACTICES INVESTIGATED WITHIN EU PROJECTS [58]

The findings are enveloped by synthesising projects' research maintenance concepts and relevant industrial applications to answer the RQs according to the available meta-data. Because projects are dedicated to the research of different maintenance philosophies and different layers of abstraction (operational, tactical and strategical), the thesis' author argues that CBM and PdM are not the same, especially in the pre and post-Internet-of-Things (IoT) era [60], [61]. Besides traditional corrective (CrM) and preventive (PM) maintenance, where PM consists of Time-Based and Condition-Based Maintenance (CBM) that uses maintenance (failure) data, PdM, on the other hand, implies CBM (diagnosis and prognosis) aspects but relies on control (process) data for MDM. Hence, if the research within the project emphasises PdM or CBM approach but relies on failure data, the strategy is noted as PM-CBM. However, if the project deals with the research on prognosis/diagnosis but relies on control (process) data, then the strategy is abstracted as PdM-CBM research. The development of sensor technology, remote monitoring (e-maintenance[62]), and typologies suggested by Veldman et al. [63], inspired the author of the thesis to propose this maintenance juxtaposition. Likewise, the "semantics" of maintenance approaches are important since various concepts are utilised and researched within the projects. For instance, Structural Health Monitoring (SHM), Prognostics and Health Management (PHM), e-Maintenance, and other approaches, depending on the decision-making level under which they are researched, are included in the study. After evaluating and categorising maintenance concepts across industrial domains, the analysis shows the following.

Figure 10 shows that projects are dedicated most commonly to SHM and PdM-CBM research philosophy, especially in the aerospace, infrastructure, railways, petroleum and manufacturing sector. Although SHM has been mostly utilised in the infrastructure and aerospace domain for structural damage detection in recent years, PdM-CBM concepts are mostly applied in energy-transfer utilities, railways, and most notably in the manufacturing sector, relying on vibration acoustic data, mainly for prognostic purposes. Prognostics and Health Management (PHM) research is mostly applied in energy transfer utilities such as wind turbines, supporting the rise of literature papers on this topic. The rise of projects regarding PdM-CBM in energy transfer dealing with signal processing in real-time overlaps with the PHM concept, however, depending on the level of decision-making – strategic, tactical or operational level. Even though the evidence provides various maintenance approaches across different industrial sectors, none of the projects was explicitly dedicated to energy-oriented maintenance practice after evaluation.

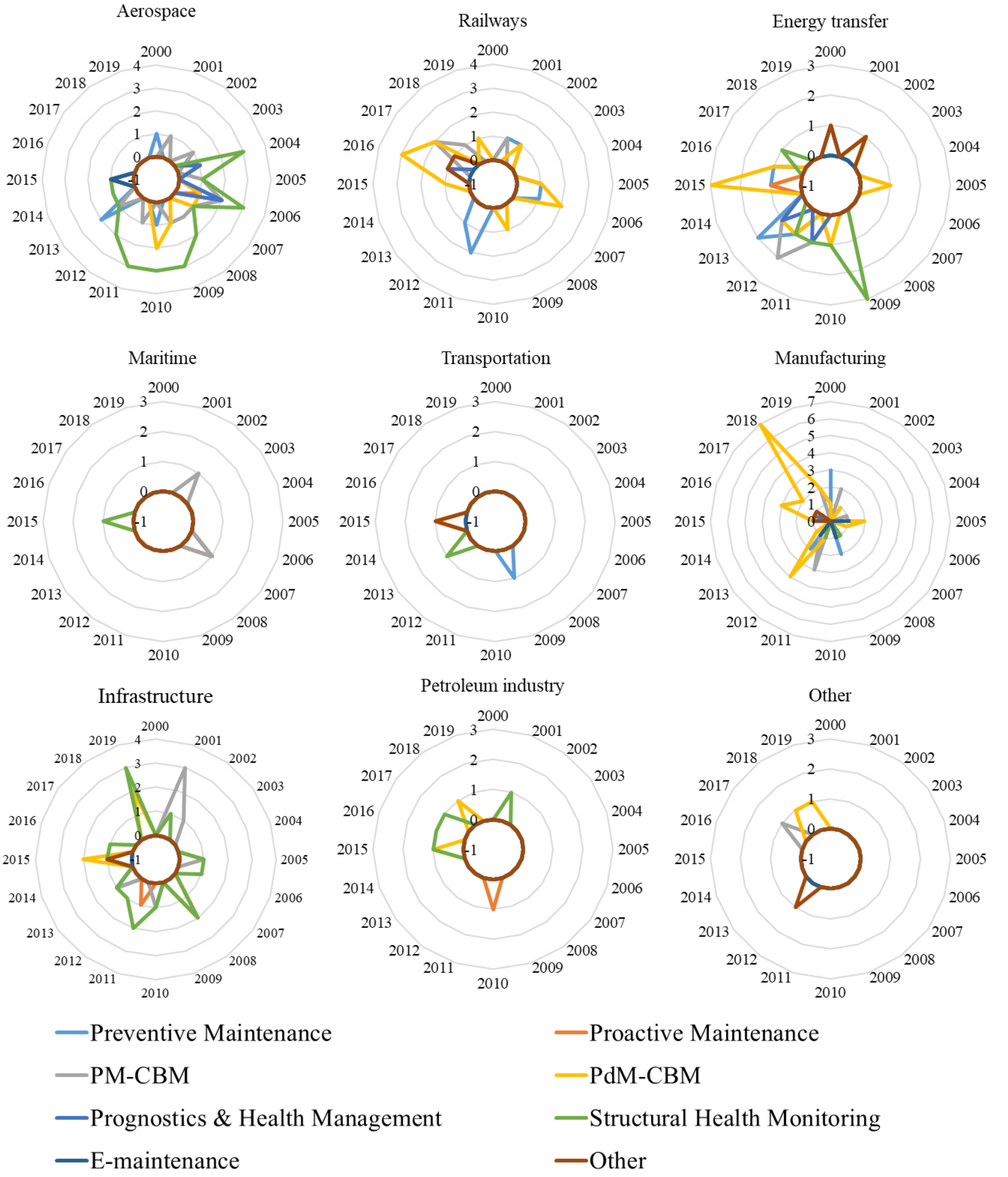
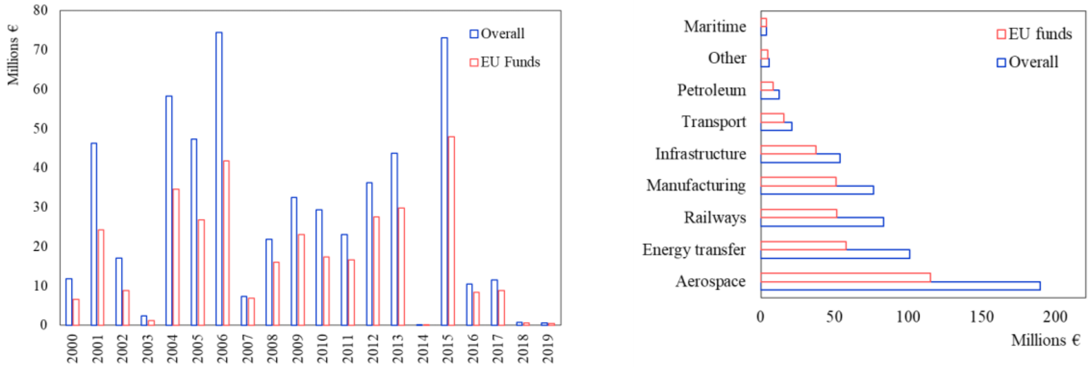


Figure 10. Maintenance approaches across industries by year [58]

Regarding the project report data, we depict the following statistics via charts. Figure 11a shows peaks of projects funds realised and 548 million Euros spent on the R&I industrial maintenance projects (347 million Euros co-funded by the European Commission). Besides, projects realised by 2010 had significantly higher investments; however, projects realised after 2010 had lower initial investments and lower co-funds but had a higher research impact. Moreover, another worrying statistic is that in comparison with the total budget of 161,5 billion Euros from FP5 to FP8 (H2020) [64], [65], industrial maintenance received no more than 0,2118% of the total R&I budget.



(a) (b)

Figure 11. Analysis of projects' research fundings by year (a) and funds by industry (b) [58]

The most significant funds for the research were spent on research within the aerospace, energy transfer (mostly wind turbines' research), railways and manufacturing industry, as shown in Figure 11b. Regarding the total budget spent on the research, the three most funded projects (more than 30M €) were in aerospace (2 projects) and energy transfer (1 project) applications.

3.2 SCIENTIFIC CONTRIBUTION AND IMPACT OF EU PROJECTS [58]

Project report data concerning the elements of scientific deliverables and funds invested in the research were collected and filtered. The elements are quantitatively expressed to investigate the actual impact of the research projects' outcomes and funds invested in the research to make a more straightforward approach in delineating the projects with actual scientific deliverables and projects that are more biased towards the educational aspect and structural repair, thus lacking original scientific contributions.

3.2.1 PROJECTS RESEARCH RESULTS AND DISSEMINATION ACTIVITIES [58]

As proposed by the question, the collected data considering scientific deliverables and dissemination activities are filtered and processed. The included deliverables and dissemination activities were extracted using CORDIS, OpenAIRE, and Google scholar, illustrated in Figure 12a. Data show that projects' results consist of conferences (458), journal peer-review articles (438), technical reports (304), patents (79), doctoral thesis (66), book chapters (17), books (12), and other deliverables (185). Additionally, no research outcomes were found for 21 projects after searching all the repositories. Figure 12a also shows that most research results are in conference proceedings and peer-review articles, lacking original contributions such as doctoral thesis and patents. Figure 12b shows that most research projects are mainly conducted in aerospace and manufacturing sectors, whereby aerospace doubles the research funds (Figure 11b). Reflecting on the evidence collected, most of the projects dedicated to producing patents as a research deliverable (40/175) do not have scientific dissemination such as doctoral thesis and peer-review articles, thus, suggesting that the research is industry-oriented. On the other hand, projects with a doctoral thesis (22/175) as a research deliverable show almost three times the number of peer-reviewed articles compared to the hypothesised industry-oriented projects.

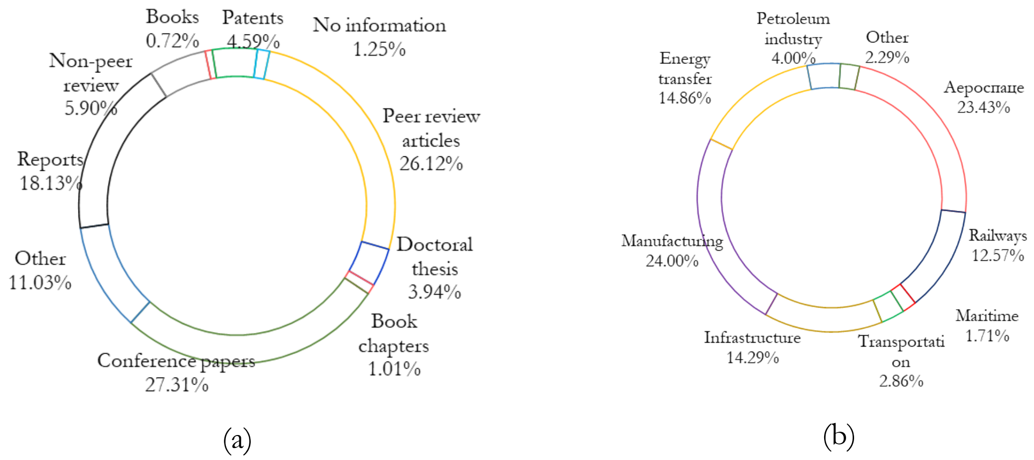


Figure 12. Analysis of projects' research results (a) and industrial application (b) [58]

Figure 13 shows the rise of workshops and conference publications, while on the other side, there is a drop in peer-review articles and doctoral dissertations (from 2011to 2017). There is also a slight rise in projects' technical reports and non-peer review articles questioning the projects' outcomes. Results between 2014 and 2016 show more workshops than published peer-review papers. Interestingly, the rise of patents has been noticed in the last decade, suggesting higher quality in industry-oriented solutions. This propensity for academic patent inventions is arguably related to the crucial role of industry-university partnerships [65], although questioning the quality of inventions compared to financial returns [66].

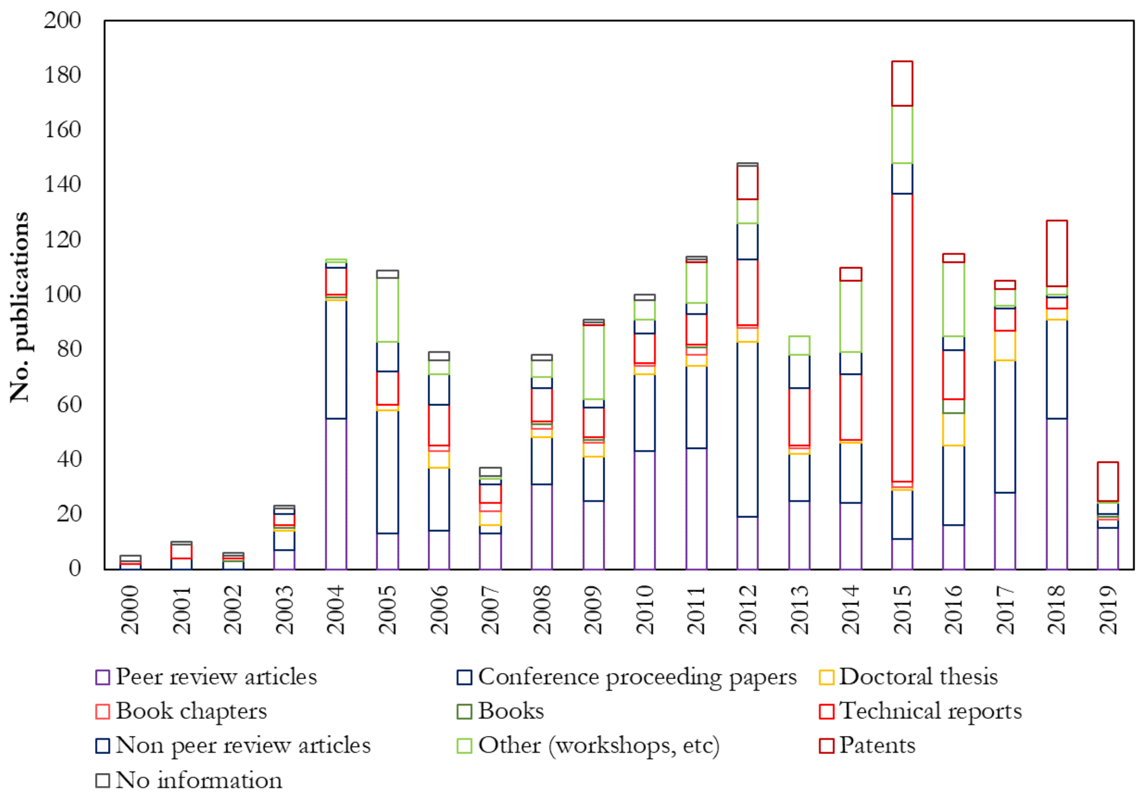


Figure 13. Maintenance projects' dissemination activities and deliverables by year [58]

3.2.2 QUANTIFICATION OF PROJECTS' RESEARCH OUTCOMES [58]

The Cronbach's α is used for reliability analysis for internal consistency for the analysis's components. A higher value (above 0.7) shows strong reliability, while in our case, ranges between 0.5 – 0.7 show moderate reliability for the internal consistency of items [67]. Furthermore, the Pearsons' correlation test is used to comprehend the relationship between variables investigated. Values above 0.7 indicate a strong relationship (correlation) between variables, while values within 0.3-0.7 indicate a moderate relationship. Before conducting a correlation analysis, the first task is to divide projects into groups due to their research motivation. The projects are divided into three groups based on the scientific deliverables: (1) projects with patents; (2) projects with doctoral theses; and (3) projects that do have patents nor theses as deliverables. The primary dependent variable is the general funds (OF) invested in the research project. The independent variables include peer-review journal articles (PRJ), conference proceeding papers (CP), doctoral thesis (DT), book and book chapters (BC), patents (PAT) and workshops/seminars (WS). Considering all meta-data collected besides research deliverables, the project's length (LE) and the number of institutions (INST) are also included.

In Table 7, the first *Pearson's* correlation matrix shows that the number of institutions involved in the project has the highest correlation (r = 0.912) with the amount of funding, followed by conference proceedings (0.717) and doctoral thesis (r = 0.580), besides lower p-value book chapters (r = 0.461) also show significant correlation with the amount of funding invested. The results also show a relatively high positive correlation between independent variables. For instance, the project duration tends to include more workshops within the project outcome, assuming to increase the project impact. The number of partners (institutions) involved in the project shows a tendency to produce more conference papers (r = 0.599), doctoral thesis (r = 0.610) and book chapters (r = 0.520, $p < 0.05$). The production of the doctoral thesis within this particular project shows a tendency with workshops hosted (r = 0.551) and books (r = 0.600), while the output of books/chapters output shows a high correlation with doctoral dissertations (r = 0.798).

Table 7. Correlation matrix for projects having a doctoral thesis as a research deliverable [58]

	OF	PLE	INST	PRJ	CP	WS	DT	BC
PLE	0.408*							
INST	0.912***	0.399*						
PRJ	0.140	0.217	0.053					
CP	0.717***	0.193	0.599***	0.475**				
WS	0.159	0.417*	0.331	0.089	0.175			
DT	0.580***	0.176	0.610***	0.099	0.530**	0.551***		
BC	0.461**	0.244	0.520**	-0.010	0.297	0.600***	0.798***	
PAT	-0.100	-0.124	-0.111	0.023	-0.180	-0.123	0.000	-0.125

Note: Chronbach's a = 0.54 value, showing moderate relationship. For two-tailed test and degrees of freedom v=20, correlations are significant at $*p<0.1$; $**p<0.05$; $***p<0.01$ (two-tailed), respectively.

Considering projects dedicated to industrial-oriented solutions, i.e., patent deliverables (Table 8), results show the following. The number of institutions (r = 0.930), patent deliverables (r = 0.745), followed by project duration (r = 0.574), show the highest correlation to the funds invested, which is reasonable considering the aims of the project. However, there is also a high correlation between independent variables. For instance, dissemination activities such as conference papers (0.789), workshops hosted (0.648), and most notably, book chapters (0.954) show a tendency to produce more peer review articles and vice versa. It is plausible to expect that patent results have been communicated to increase the scientific impact through various dissemination activities.

Table 8. Correlation matrix for projects having a patent as a research deliverable [58]

	OF	PLE	INST	PRJ	CP	WS	DT	BC
PLE	0.574***							
INST	0.930***	0.450***						
PRJ	-0.015	0.366**	-0.006					
CP	-0.003	0.327**	-0.058	0.789***				
WS	0.251	0.427***	0.289*	0.648***	0.771***			
DT	0.091	0.178	0.089	0.261*	-0.042	-0.077		
BC	-0.076	0.293*	-0.048	0.954***	0.817***	0.694***	-0.026	
PAT	0.745***	0.578***	0.633***	0.227	0.254***	0.343**	-0.082	0.210

Note: Chronbach's a = 0.57 value, showing moderate relationship. For two-tailed test and degrees of freedom v=38, correlations are significant at *$p<0.1$; **$p<0.05$; ***$p<0.01$ (two-tailed), respectively.

In Table 9, the results show that the most significant factors within the correlation of overall funds invested in the research with $p < 0.01$ are the number of institutions involved ($r = 0.726$), project length ($r = 0.546$), workshops ($r = 0.382$), and conference publications ($r = 0.288$), respectively. The correlation between independent variables shows a high correlation between project duration and the number of institutions ($r = 0.494$), conference publications ($r = 0.320$) and published peer-review articles ($r = 0.302$), and workshops ($r = 0.197$; *p-value* < 0.1). The tendency to publish more papers in peer-review articles and conferences is linked to the number of institutions involved in the project. As a consequence of projects that do not include a thesis or patent as a research deliverable, the theoretical probability of hosting workshops is relatively high compared to other deliverables. Although the causality is difficult to prove and is beyond the scope of this article, however, the presence of a statistically significant ($p < 0.01$) correlation between funds and the number of workshops held suggests a lack of original scientific advancement in industrial maintenance technology in terms of primary (original) source articles.

Table 9. Correlation matrix for projects without a thesis or patent [58]

	OF	PLE	INST	PRJ	CP	BC	TR
PLE	0.546***						
INST	0.726***	0.494***					
PRJ	0.168	0.302***	0.229**				
CP	0.288***	0.320***	0.279***	0.467***			
BC	-0.033	0.122	0.045	0.040	0.092		
TR	0.053	0.106	-0.010	0.021	0.266**	0.158	
WS	0.382***	0.197*	0.352***	0.047	0.578***	-0.035	0.028

Note: Chronbach's a = 0.61 value, showing moderate relationship. For two-tailed test and degrees of freedom v=90, correlations are significant at *$p<0.1$; **$p<0.05$; ***$p<0.01$ (two-tailed), respectively.

3.2.3 PUBLICATION WEIGHT FACTOR [58]

A quantitative scale of disseminated activities is proposed after evaluating the project research outcomes compared to the funds invested in the research. The underlying reason for proposing such a quantitative estimation measurement abstracted as Publication Weight Factor (PWF) is to highlight industrial maintenance research projects' scientific and technological contributions considering all research activities for which the project(s) have been funded. Therefore, by referring to the Rulebook that evaluates the quality of scientific contribution by quantitative expression of research results proposed by the Ministry of Serbia as a part of the Law on Scientific Research Activity [68], the PWF is elaborated. The proposed *R* values (Table 10) within the Rulebook are expressed as integer values according to the rank of the scientific publications proposed.

Table 10. Respected *R* values for quantitative estimation of research deliverables [58]

	***R* values**				μ_{Rij}	σ_{Rij}
Category	R_1	R_2	R_3	R_4		
PAT	16	12	9	7	11	3.916
PRJ	10	8	5	3	6.5	3.109
BC	7	4	2	1.5	3.6	2.496
CP	3.5	1.5	1	0.5	1.6	1.315
DT	6	6	6	6	6	0

The *K* (X_{Rij}) values are determined by the ranking (R_j) of the deliverables category respecting their quality and contribution. The values can be referenced in the proposed Rulebook [69]. The following equation for transforming *R* values into Q^R values is proposed to validate the ranking according to their respected position compared to other research deliverables by relying on projects' factsheets and meta-data.

$$Q_{ij}^{R} = \frac{X_{R_{ij}}}{\sum_{j=1} X_{R_j}} . \tag{3.1}$$

Where X_{Rij} represents values according to the type of publication *i* and ranking *j*. Hence, the PWF is determined by the average of ranking category values Q_i for the type of publication *j* as:

$$PWF_{Q^R} = \frac{1}{n}\sum_{i=1}^{n} Q_i^R . \tag{3.2}$$

Finally, the given values are represented in the following Table 11, and the same is used for quantitatively representing the actual scientific and technological impact of maintenance-related research projects concerning their overall investment.

Table 11. Determined Publication Weight Factor for research deliverables [58]

	Q_1^R	Q_2^R	Q_3^R	Q_4^R	Sum_{Qi}	PWF_{Qi}
PAT	0.376	0.381	0.391	0.389	1.538	0.384
PRJ	0.235	0.254	0.217	0.167	0.873	0.218
BC	0.165	0.127	0.087	0.083	0.462	0.115
CP	0.082	0.048	0.043	0.028	0.201	0.050
DT	0.141	0.190	0.261	0.333	0.926	0.231

Based on the proposed PWF values for *j* type of publications, the expected score of all industrial maintenance EU funded projects shows an average μ_{PWF} = 1.024 and σ_{PWF} =2.021. Average PWF shows that only 43/175 projects are higher than the average value. Hence, the correlation between Publication Weight Factor – PWF (Figure 14) and overall funds of R&I projects for assessment is additionally screened and charted. However, a stochastic correlation can be seen; most successful projects' PWF is up to €5M R&I funds, though projects above €5M show a drop in PWF. Concerning the type of projects proposed individually, the average values are the following: for projects with patents is $\mu_{PWF\text{-}PAT} = 1.063$; for projects with a doctoral thesis, $\mu_{PWF\text{-}DT} = 2.756$; and for projects only with publications, $\mu_{PWF\text{-}PUB} = 0.578$. Finally, to make a more straightforward approach to presenting actual scientific achievements than the total funds invested, the correlation between overall funds and PWF of the proposed project groups is plotted in Figure 14. The evidence suggests that the most successful projects in terms of PWF and funds invested are within 2M-5M € of overall funds. It can be noticed that PWF does not increase after the investments of 5M €. On the contrary, projects without a thesis or patent seem to drop, while workshops and seminars within project activities tend to rise. It should be noticed that the use of PWF of research deliverables is only used as a point of reference by comparing the amount of research contribution, and later on, to objectively compare the PWF with currently active research, for instance, sustainable manufacturing projects.

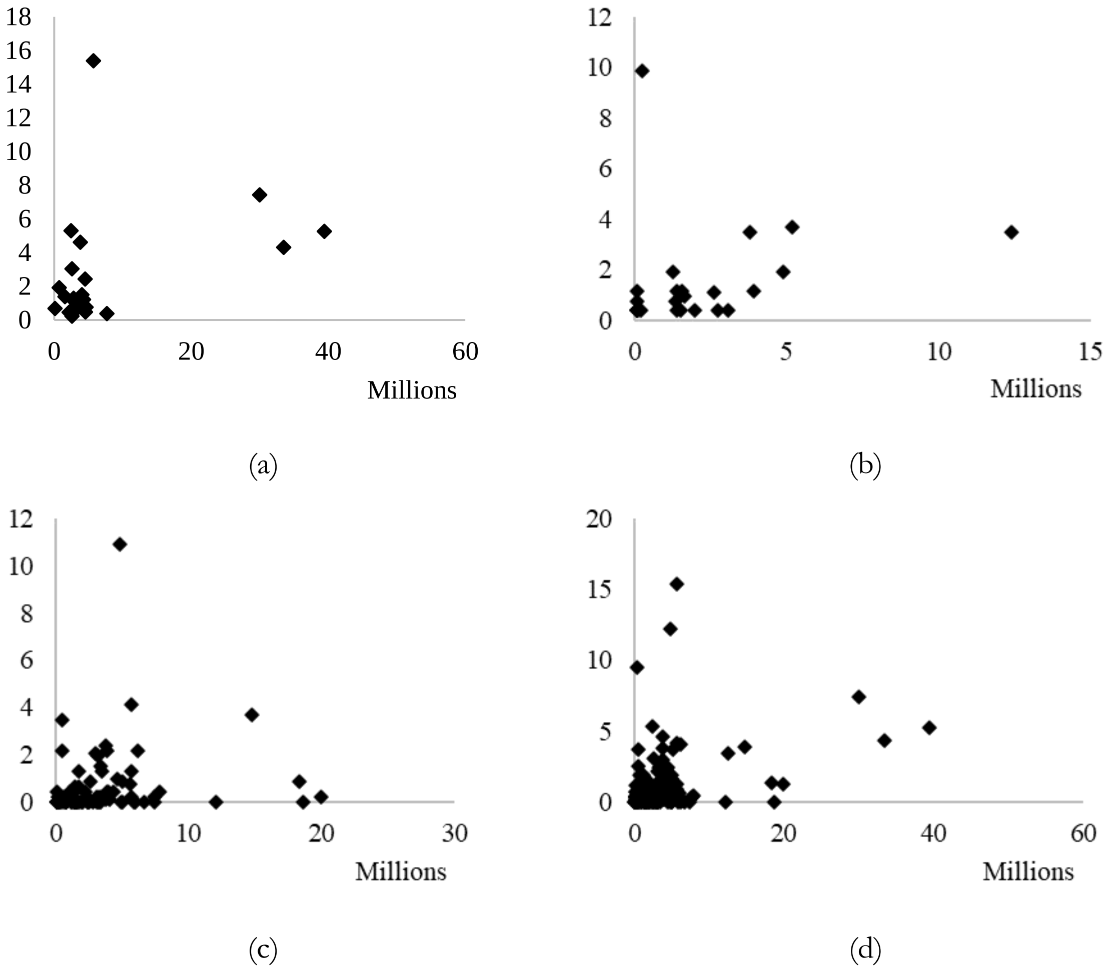


Figure 14. Correlation between PWF (*y*-axis) and overall funds (*x*-axis): (a) projects with doctoral thesis; (b) projects with patents; (c) projects without thesis and patents; (d) all industrial maintenance-related projects [58]

Finally, we turn towards the geographical project assessment to illustrate the uneven scientific contribution of maintenance-related EU projects. Using available meta-data, we present the following evidence. Institutions that have participated in EU maintenance projects (Figure 15) [*as coordinator%*; *as partner%*] are from United Kingdom [18,29%; 14%], Germany [13,71%; 13%], France [9,71%; 13%], and Spain [16%; 9%]. The rest of the countries showed the following: Italy [8,57%; 8%], Greece & Belgium [4,57%; 6%], Sweden [2,29%; 4%], Netherlands [5,71%;3%], while below 3%, are institutions from other countries, as coordinator and partner, respectively.

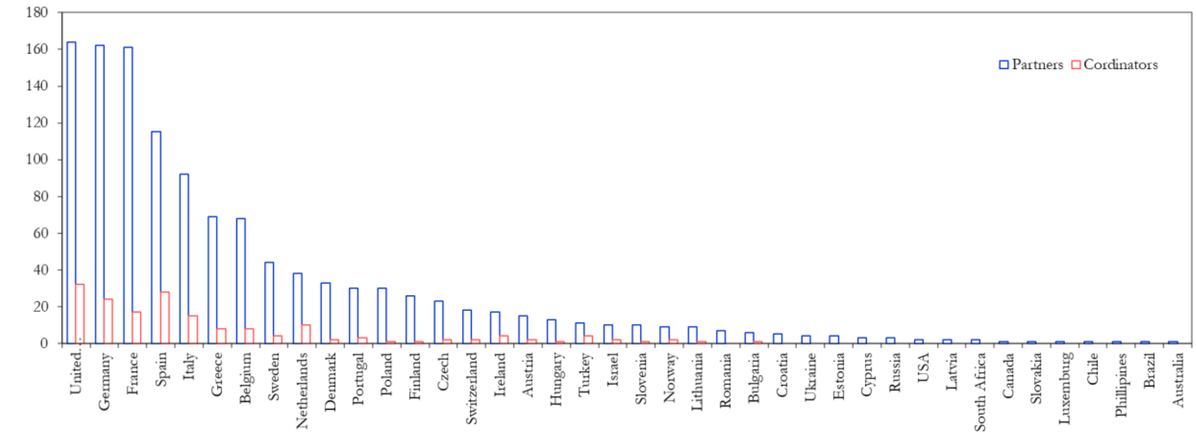


Figure 15. Institutions from countries that participated as partners and as coordinators (*x*-axis) and number of projects (*y*-axis) [58]

Investigating the research interest of EU countries by associating the projects' particular industrial domain and countries involved (Figure 16), it can be seen that western EU countries mostly dedicate their industrial maintenance research to aerospace, manufacturing, energy utilities and railway sector. Interestingly, all countries' research involves research within the manufacturing sector, whereas Germany and Spain have the most projects associated with the sector.

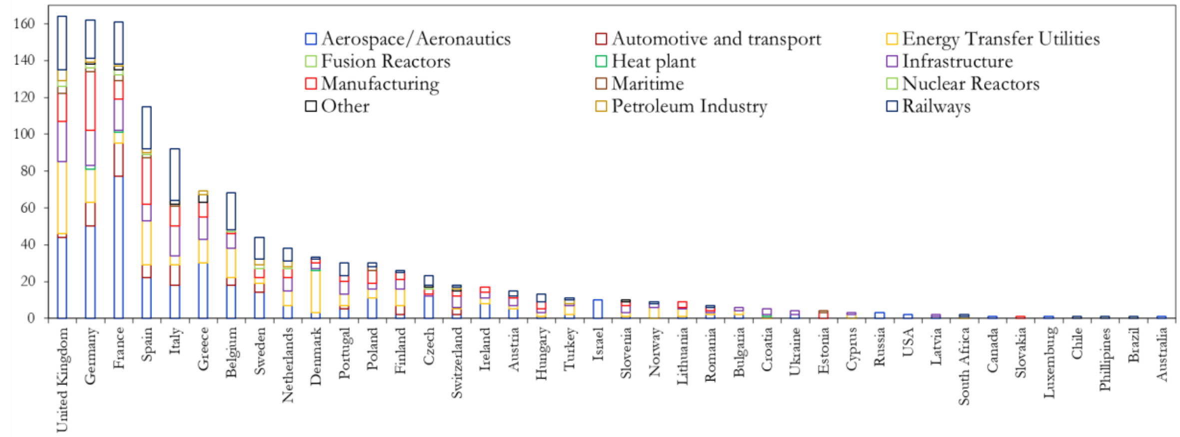


Figure 16. Representation of countries that participated in the project (*x*-axis) within the industrial domain of research (*y*-axis) [58]

Figure 17 illustrates that industrial maintenance research in the last 20 years has been mostly conducted in Western European countries, highlighting the correlation between research technological achievements and the "Iron Curtain" dichotomy. Taking into account that the quality of industrial maintenance (e.g. analytical tools, knowledge, instruments) is highly dependent on the industrial technology whose activities are conducted by knowledge of machine failure mechanisms, however, evidence shows a lack of proper scientific and engineering research support and capacity on the other side of the Iron Curtain.

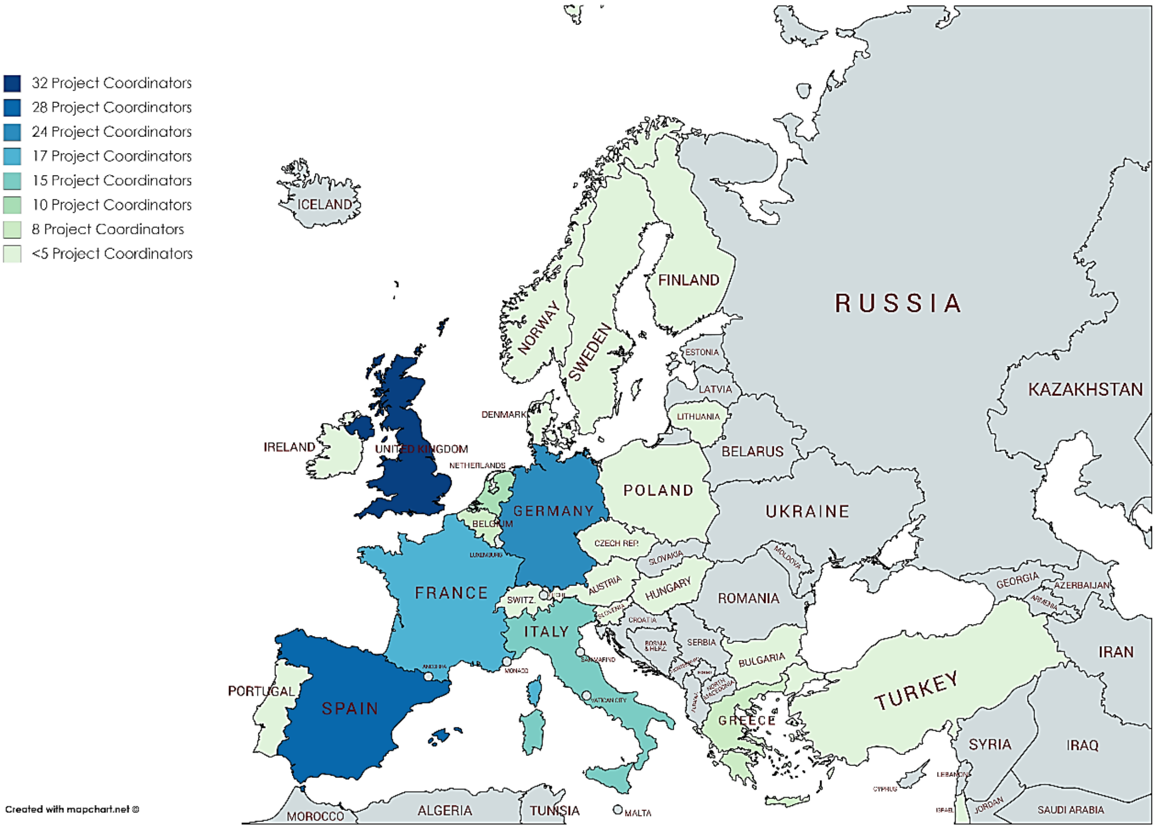


Figure 17. Maintenance-related research projects and institutions coordinators [58]

3.3 Remarks and implications

Evidence from R&I projects provides an exciting insight into the state of practical and academic scientific research of industrial maintenance in the EU. Still, it implicitly shows a lack of achievement and inconsistency with ongoing maintenance research propositions due to various reasons.

(1) Technological progress is mostly present in western countries, while scientists in eastern countries are more involved in research as research critics. Hence, to flatten the technological landscape by reducing the apparent differences between socio-technological entropies, future R&I funds for maintenance projects must, on one side, focus on gentrification and technology transfer activities in non-associated countries and on the other on improving PWF dedicated to energy-oriented maintenance research.

(2) With the emergence of Green Deal targets and the probability of getting outside the continental level, maintenance academicians and industrialists must understand the sustainability aspect's importance as a vital MPI. Although it may sound like a simple task for maintenance, the literature shows that it will become a complicated ordeal due to the lack of maintenance scientists in the data science domain.

(3) Present maintenance indicators such as cost and availability are that the scientific research direction is still relying on reducing costs; therefore, no projects were found to deal with the sustainability issues in the maintenance research domain, thus emphasising that this kind of research proposal is yet to be expected.

(4) The overall conclusion of the research data shows the drop in scientific deliverables, such as primary research studies (e.g., doctoral thesis and original studies), which is the reason why imposing a new paradigm shift could help improve and provide a rationale for improving original scientific production of papers in industrial maintenance domain.

4 STATE-OF-THE-LITERATURE RESEARCH RESULTS

Until World War II, the industry was highly mechanised, machines were mostly robust, and the consequences of failure, at the time, were not considered a severe threat to gaining profit [4]. Operational management usually underestimates maintenance, stating that the costs are accidental rather than controllable [70]. However, when academics began to impose maintenance strategies for improving operational performance, maintenance technology gained significant interest in reducing production losses. The Peter Jost report (1966 [71]) stresses that the UK loses between 1,1 – 1,4 GDP due to friction and wear. Likewise, in a postdictional paper [72], Holmberg & Erdemir state that 23% of the world's global energy consumption is needed to overcome friction and wear, thus highlighting the much-needed involvement of maintenance technology. Gaining attention from the general public, maintenance managers and engineers firmly focused on reducing these losses in time and money, overlooking the energy factor. The absence of sensors and sophisticated data-acquisition techniques was the hindsight of neglecting energy as an indicator. Hence, giving a brief overview of the maintenance of the pre- and post-Internet-of-Things (IoT) era [60], [73] will contribute to the originality of the proposed solution. The development of sensors (e.g., RFIDs and MEMS), and analytical tools to process data, often remotely, served as an apparatus to illustrate and validate why such maintenance cohorts are proposed.

4.1 TRADITIONAL MAINTENANCE STRATEGIES – 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 that 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*"[27]. The BSI definition of maintenance implicates two basic maintenance strategies by whom most researchers oblige: Corrective Maintenance (CrM) and Preventive Maintenance (PM) [63], [74]–[76]. The CrM is also known as run-to-failure (RTF) or reactive maintenance, while PM consists of Time-Based Maintenance (TBM) and Condition-Based Maintenance (CBM). Although academics usually attach RTF with CrM to the author's knowledge, it can be highly debatable depending on the complexity of a system or organization. Although it is beyond the scope of the thesis, the author would like to draw attention, for the sake of clearness, that RTF can indicate CrM but not the other way around. The RTF uses the proposition of replacing the parts when they reach a total failure state, and there is no methodology or spare parts, logistics, or any other layer of MDM. The CrM, on the other hand, is a form of a strategy that is in use even today, which uses strategic planning, tactical decision-making and operational activities of calculating appropriate replacement decisions, spare parts inventory, stocks estimation, and cost-benefit analysis.

Unlike the CrM approach, where the goal was to coupe with the consequences of the failure, the PM dedicates to finding and preventing, or in other instances, reducing the frequency of failures. The CrM 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 the expectations, making PM (TBM and CBM) more compelling. Regardless, TBM provided opportunities to improve operational efficiency and eventually have a hard time fulfilling the needs of more complex and sophisticated systems. Leveraging stoppage' expenses while conducting maintenance activities and preventing failures, maintenance optimisation became an extensively popular topic [6], [77].

The maintenance optimisation era forced peers to shift more attention to optimal strategies and tactics, 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],

[77] and mostly due to disruptive technologies. Some argue that CBM was introduced in 1975 [78], 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 [79]. The exceptionality of CBM became apparent in its unique way to reduce unnecessary activities by taking action only in the case of abnormality. Although lacking proper characterisation, the CBM became extensively attractive in practical and academic circles. Eventually, Jardine et al. [80] 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 applied only when acquired data shows abnormal behaviour. For CBM to be effective, Jardine argues that two data types are required: event data (e.g., repair or preventive actions) and monitoring data (e.g., temperature and pressure). Interestingly, the CBM is considered the same as PdM by various authors [4], [63], [78], [79]. The author of the thesis argues that this could be a misconception and misinterpretation of the terms because different underlying concepts drive each of the methodologies to different goal-oriented objectives.

4.2 MAINTENANCE STRATEGIES – POST IOT ERA

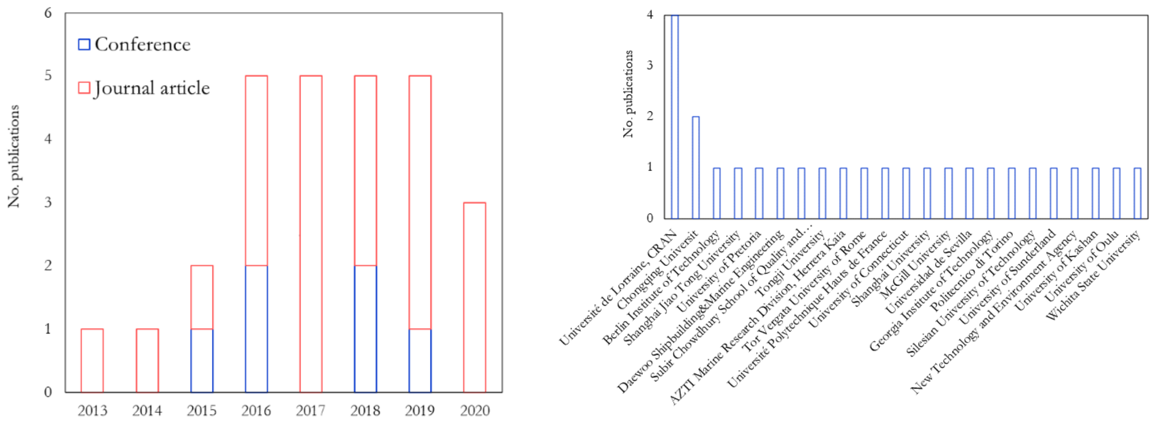
The author proposes that CBM is not identical to PdM to present the claims. Similarities exist to some extent; however, although PdM somewhat implies CBM (diagnosis and prognosis), it does not address the same processing data. Namely, the CBM program belongs to preventive and predictive maintenance strategies, stated herein as PM-CBM and PdM-CBM, respectively. The first aspect of CBM, the diagnostic aspect [81]–[83], or Fault Detection and Isolation (FDI) [84], [85] ex. RCA (Root Cause Analysis) [86] deals with fault detection, isolation and identification when a failure occurs. Conversely, prognostics deals with fault anticipation, i.e. providing decision support before the failure occurs. These two aspects frame the CBM program [63], [74], [80], [87], 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, however, mostly focus on the prognostics aspect [88]–[93], especially the Remaining Useful Life (RUL) prediction. Prognostics evaluate the historical diagnosis results and anticipate the RUL of safe operation, relying mostly on statistical approaches [79].

With that in mind, the PM-CBM approach to conducting maintenance activities relies mostly on failure data with statistical or analytical modelling to predict and perform needed actions. For instance, using Cox's Proportional Hazard Modeling in PM-CBM emphasises high dependence on failure data for diagnosis [74], [94]. Conversely, PdM-CBM relies more on process control data (e.g., vibration, noise, temperature) to predict the impact on operational performances. In this particular realm of maintenance (PdM-CBM), PCA (Principal Component Analysis) gained prominence after the 2000s [95], [96] for determining the replacement control limits. More recently, the method of PCA has been applied in manufacturing [97], aerospace industry [98], and infrastructure [14], also extended with an unsupervised machine learning approach [11]. The development of sensor technology, remote monitoring (e-maintenance[62]), and typologies suggested by Veldman et al. [63], inspired the author to propose this maintenance juxtaposition. Likewise, numerous programs exist within the literature; for instance, PHM (Prognostics and Health Management) program extends the traditional CBM's diagnostic and prognostic aspects with LCM (Life Cycle Management) capabilities. Some authors consider PHM a synonym for CBM [85], [99], although without proper terminological explanation to support such claims. Similarly, the SHM (Structural Health Monitoring) program closely reflects CBM. Only the condition-monitoring part of CBM emphasises structural damage detection. The SHM has been widely applied in aerospace [100], civil [101]–[103], and mechanical engineering structures [104]. Unlike many condition-monitoring techniques that CBM and PHM consist of, the SHM [105], however, mostly relies only on vibration or noise data for pattern recognition [106], with more details in the diagnostic aspect [107]. Putting all together, one can conclude that SHM and CBM closely relate to each other, with differences in analysis and layer of decision-making since SHM mostly encompass the tactical layer, while CBM encompasses mostly the strategic layer. Although, unlike SHM, recently, the PHM has extended the CBM program with LCM. This is a question of debate and is observed by the rise of review papers focusing on the proper classification of various CBM techniques resembling secondary source literature. However, these strategies resemble a practice in which decision-making and maintenance activities are provided to avoid failures using non-primary energy-induced indicators like vibration or sound. The prospect of EBM focuses more attention on input-output energy usage and waste in which functionality is observed by monitoring deviations within the same.

4.3 ENERGY- AND SUSTAINABLE-ORIENTED MAINTENANCE RESEARCH

4.3.1 META-DATA OF PUBLICATIONS [58]

Results show the following from the systematic EBA approach of synthesizing papers relevant to the study. In sum, 27 articles are included for the analysis (Figure 18a). Firstly, it was discovered that 16 out of 27 studies were carried out on institutions or universities from Europe, following China, the US and others (Figure 18b), mostly at the University of Lorraine, by Hoang et al. [23]–[25], [108].



(a) (b)

Figure 18. Meta-data of (a) publications and (b) studies conducted by institutions [58]

Secondly, concerning industrial applications and maintenance policies (Figure 19), the evidence suggests that most studies were dedicated to the manufacturing applications (13 studies) and case studies on the TELMA platform [24] (4 studies), while most of the other applications were relying on specific case study (e.g., motor, pump) and numerical experiments (Figure 19a).

Regarding the research efforts and addressing specific points of studies, such as utilising energy performance indicators as trigger points to conduct specific corrective or preventive actions, mostly fall under the CBM. Figure 19b depicts that most of the studies encompass CBM and PM policies since energy-oriented solutions within these research studies are modelled on a lower level of decision-making such as tactical [109] and operational level [23], [110], emphasising the low maturity level for the concept of policy.

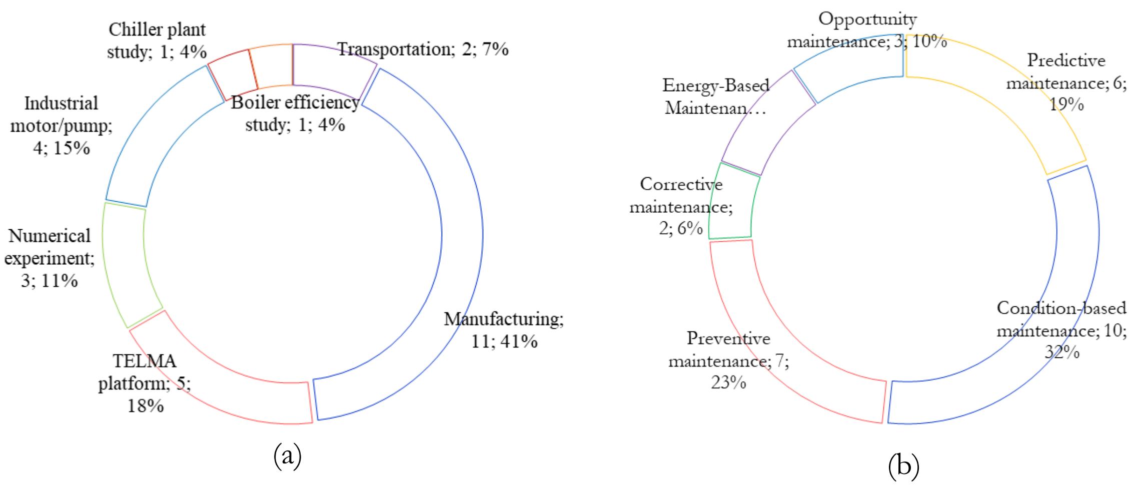


Figure 19. Analysis of application: (a) industrial sector and (b) maintenance policy [58]

Finally, content-based evidence suggests the following: (1) most of the studies utilise modelling and optimisation methods and time-series analysis and AI techniques (Figure 20a). On the other hand, Figure 20b depicts that two approaches were used for proposed models: economic and cost-benefit analysis, which is applied to validate the proposed maintenance concepts or use simple regression analysis to verify the outcome of the proposed solutions.

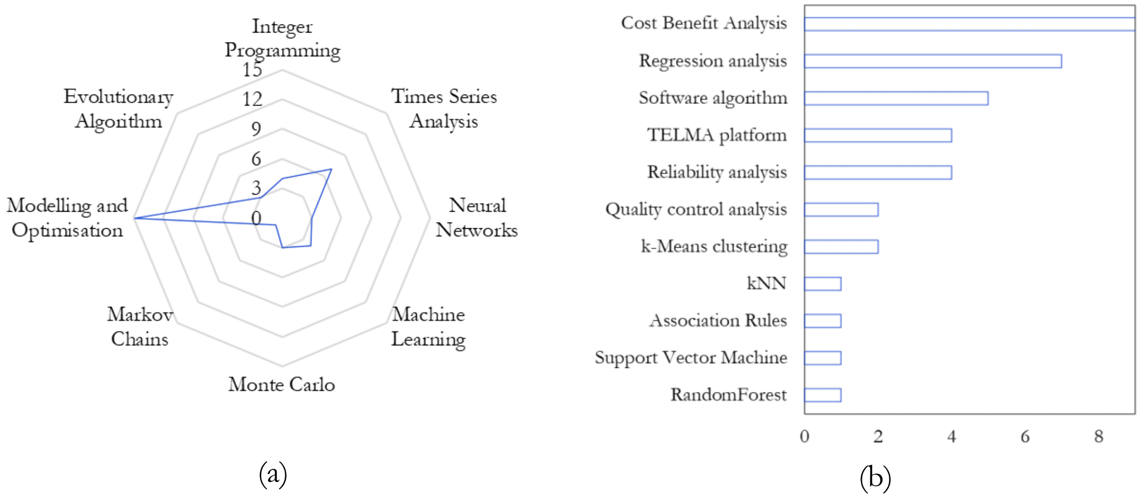


Figure 20. Systematic analysis of research: (a) methodologies and (b) source of verification [58]

4.3.2 Energy-dedicated maintenance prospects and concepts

There are a few examples where researchers started creating new models-policies, such as Sustainable Condition-Based Maintenance (SCBM) [111] and Energy-Based Maintenance (EBM) [112], encompassing a higher level of decision-making. Hence, the studies address the strategical level by proposing novel maintenance policies, including energy indicators such as CBM-ESOW (Energy Saving Opportunity Window) [113] and CBOM (Condition-Based Opportunity Maintenance) [114]) are still in the infancy stage, thus lacking practical case studies. As shown in Figure 19b, most of the EBM concepts provided rely on traditional maintenance actions (e.g., CM, PM). However, even though the concepts proposed argue that it would be beneficial to include environmental elements in such concepts, most still consider the economic/profit factor as a primary optimisation function. Nevertheless, we provide an overview of existing models and maintenance concepts, considering the effect of energy consumption, energy efficiency or related indicators for different aspects and decision-making levels of maintenance (Table 12). An in-detail discussion is given in the following sub-section.

Table 12. EBM models and maintenance concepts proposed with thresholds prospects [58]

Concept	Aspect	Application	Model/Method	Indicator/Markers	Threshold	Data	Level	Policy
MAM-ESW [115]	Optimisation	Manufacturing	Optimisation and programming algorithm. Reliability modelling.	Energy data Production data Maintenance data	Changeover/batch cycles	Failure data	Operational/ Tactical	EOM
CBM-ESOW [113]	Optimisation	Manufacturing	Algorithm. Reliability modelling. Monte Carlo.	Effective Energy Efficiency (EEE)	Gamma process ($X_j^p=\omega \cdot X_j^f$)	Failure data	Strategical	PM-CBM
E(D)-CBM [25], [108]	Prognosis/ Optimisation	TELMA platform	Cost-Benefit model. Monte Carlo simulation.	Energy/Maint. cost System availability	Fixed L threshold ($EEI_{Threshold}<EEI$)	Process data	Operational/ Tactical/ Strategical	EE-CBM
REEL [23], [24]	Prognosis	TELMA platform	Multiple linear regression. Gamma stochastic process.	Motor speed and deterioration (bearing) level.	Fixed L threshold ($EEI_{Threshold}<EEI$)	Process data	Operational/ Tactical	PdM-CBM
SCS [116]	Diagnosis	Chiller plant	k-Nearest Neighbour classifier, k-Means cl.	Power savings	H/Ca/Cr (%) fouling severity	Process data	Tactical	D-CBM
EBM [112]	Diagnosis	Manufacturing	SPRING algorithm with Dynamic Time Warping.	Electrical power intake fault-pattern	Hierarchical Agglomerative clustering	Process data	Operational	EBM-CBM
PPMP [109]	Optimisation	Manufacturing	Mixed Integer Non-Linear Programming	Production costs Maintenance costs Inventory cost Energy costs	Increase in processing time	Failure data	Tactical	PM-CBM
EEM [110]	Diagnosis	Manufacturing	Machine learning. Data mining. k-Means clustering	Energy consumption profiles	x and σ value of air consumption $x_i - 3\sigma \leq x_i \leq x_i + 3\sigma$	Process data	Operational/ Tactical	PdM-CBM
CSC-CCE [117]	Optimisation	Process plant	Energy efficiency modelling Cost Benefit Analysis.	Energy consumption Maintenance activity Failure occurrence.	-	Process data	Tactical/ Strategical	PdM-CBM
SCBM [111]	Prognosis	TELMA platform	MDM framework	Remaining Sustainable Life	Critical Sustainability Level	Process data	Strategical	CBM
CBOM [114]	Prognosis	Manufacturing	Monte Carlo simulation. Dynamic programming.	Inspection cost Maintenance cost Energy cost	(L_i)EEIL (corrective) (M_i)EEIM (prevent.)	Process data	Strategical	CBM

5 STATE-OF-THE-PRACTICE SURVEY RESULTS

As the previous paragraph goes into slight detail about the motivation for conducting the research by exploring scientific projects funded by the EU, the state-of-the-practice purpose, however, is to back up the outcome of the thesis. Namely, the general outcome is to provide an easy-to-understand sustainable maintenance paradigm for an energy-oriented society by collecting evidence from the practical machine processes. In that way, the impact of the thesis will have a larger research impact and contribution. By extracting information such as industrial machines' working conditions, work-load, type of instruments utilised, and similar, the scientific community can gain much more insight into real-working conditions and face the challenging issues extracted from the practical environment.

5.1 INDUSTRIAL AND MOBILE MACHINES DATA RESULTS

Research that provides a new solution in the hydraulic system maintenance domain is not so straightforward. The underlying reason is that results are hard to transfer to real-world operating conditions from the laboratory. The survey is used to target specific characteristics of systems for selecting the most common type for the analysis in the thesis. Besides, looking at the various suggestions from textbooks (e.g., Bosch Rexroth [118]) regarding the type of hydraulic systems utilised, it was hard to determine the appropriate experimental set-up (e.g., working conditions, flow and pressure set-up). Therefore, the main point of extracting such data is to provide a meta-evidence of real operating conditions. Results could be used in the experimental study or depicted by a distribution of operational characteristics. The survey acquisition started in May 2019, while reliability-validity testing concluded on the 31st of December 2020. The results show a 42.55% response rate, while I/E criteria excluded additional 28 companies due to lack of information, bias, validity and reliability testing. The analysis's final size is 72, encompassing 3442 hydraulic control machines (1110 industrial; 2332 mobile).

5.1.1 HYDRAULIC OPERATIONAL AND TECHNICAL DESCRIPTIVE SURVEY RESULTS

From the initial data overview, it can be seen that most of the mobile machines include excavators (Figure 21a), while stationary hydraulic systems consist of presses and CNC machines (Figure 21b). Because hydraulic control systems are high in energy consumption, most of the machines include heavy-duty machines working at a high range of pressure and flow.

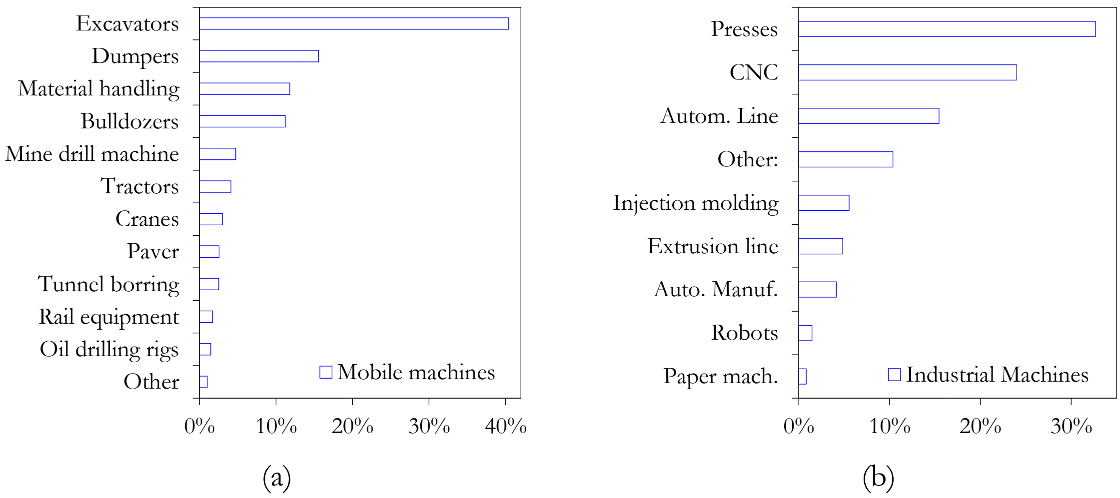
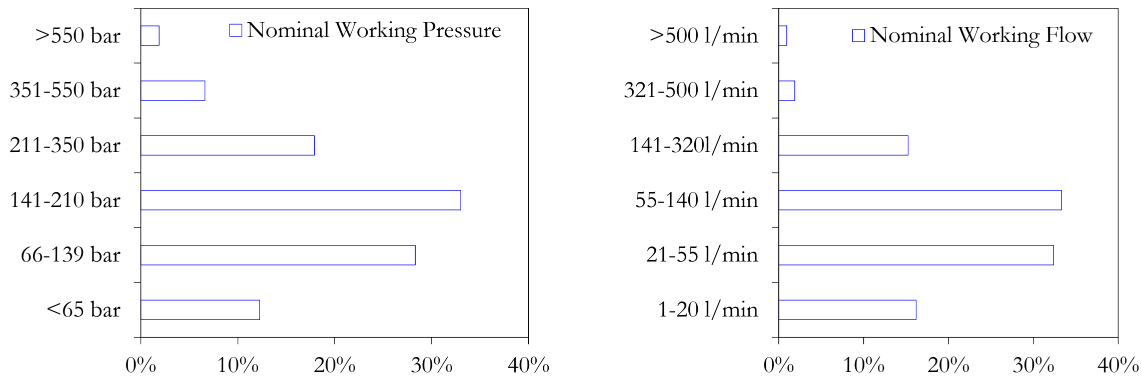


Figure 21. Stationary (a) and mobile (b) machines employing hydraulic control systems

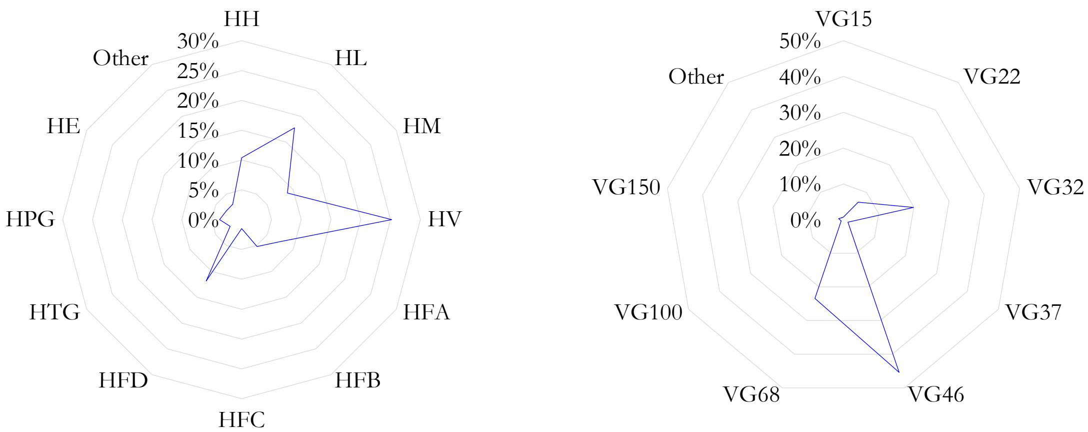
Operational characteristics of heavy-duty machines are important for gaining insight into energy consumption, workload, and intensity. Such data can be used to further justify, for instance, experimental investigation of particular pumps, oils, cylinders, and equipment for gaining the importance of such test-beds. Hence, the Nominal Working Pressures (NWP) and Nominal Working Flow (NWF) are divided into different regimes (Figure 22) and show that most of the machines are working at the range of NWP = 60-210 bars (mostly 140-210) bars, while NWF = 50-140 l/min.



(a) (b)

Figure 22. Nominal working domains of pressures (a) and flow (b)

Literature regarding the maintenance of hydraulic systems and experimentation shows the lack of data regarding the viscosity and type of fluid used. Since such data is lacking (e.g., the base oil used, viscosity, additives, viscosity index, density) and is important for conducting a study, these variables are included. It was noticed that HV, HM, HL and HFD (Figure 23a) oils are mostly utilised, while most are on viscosity grade ISO VG 46 (Figure 23b). With such data, one can gain more validation into research since it is more practically justified.



(a) (b)

Figure 23. Type of hydraulic fluid employed (a) and viscosity grade (b)

Furthermore, it is also interesting that within the sphere of experimentation, mostly on diagnostics and prognostics, while in some cases also for optimisation purposes, the lack of data regarding the size of the hydraulic system oil filling is noticeable. The lack of such evidence also forced the author to include such variables, as depicted in Figure 24. Defining critical points or allowable thresholds for determining wear of a hydraulic pump by spectrophotometric analysis given in ppm (~mg/l) largely affects the amount of fluid within the system and the wear-lag indicator that can show below-defined limit (rule of thumb for ferrous particles between 5-15 ppm). Therefore, it is also important to gain insight into this variable and search whether there is a correlation between them.

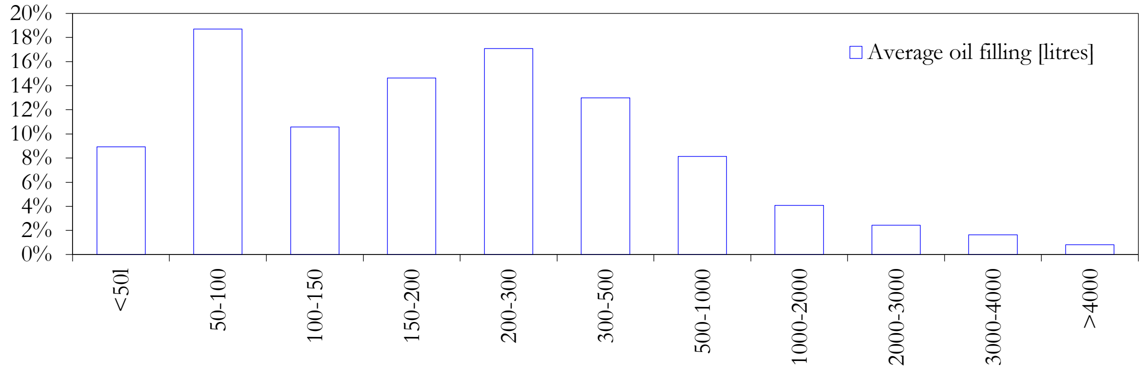


Figure 24. Hydraulic fluid fillings within the whole control system or a machine

Acquired data should serve as a descriptive notion of industrial state-of-the-practice for establishing the median or mean operational characteristics for justifying the proposed experimental design and later validation. Moreover, since operational characteristics are not large enough to gain insight into the current state of the practice, maintenance performances, activities and indicators are also used to evaluate the type of failures, programs, and associated activities and are represented in the following. Such data is used to gain insight into market-maintenance intelligence and technology for concluding whether the market is available for accepting radical changes in sustainable practice.

5.1.2 Maintenance practice descriptive survey results of West Balkan

The author considers that top maintenance management often misunderstood and misinterpreted most maintenance practices, leading to inadequate strategy, maintenance actions, and logistic support. The author surveyed the top management of various companies employing a hydraulic system to support such a claim. The results show that the maintenance policy is still poorly developed (Figure 25a). Looking at the programs utilised within various maintenance policies, the chart (Figure 25b) shows that most companies rely only on visual conditioning and inspections (41%).

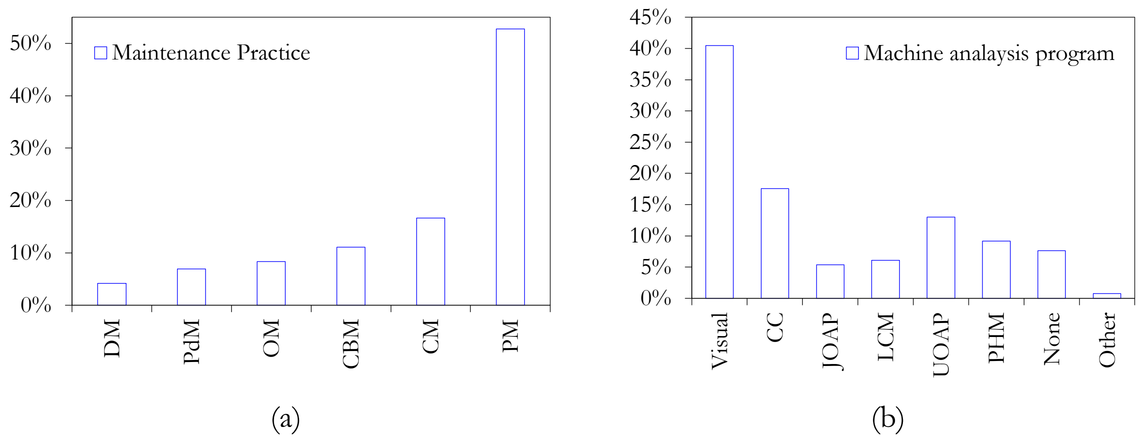
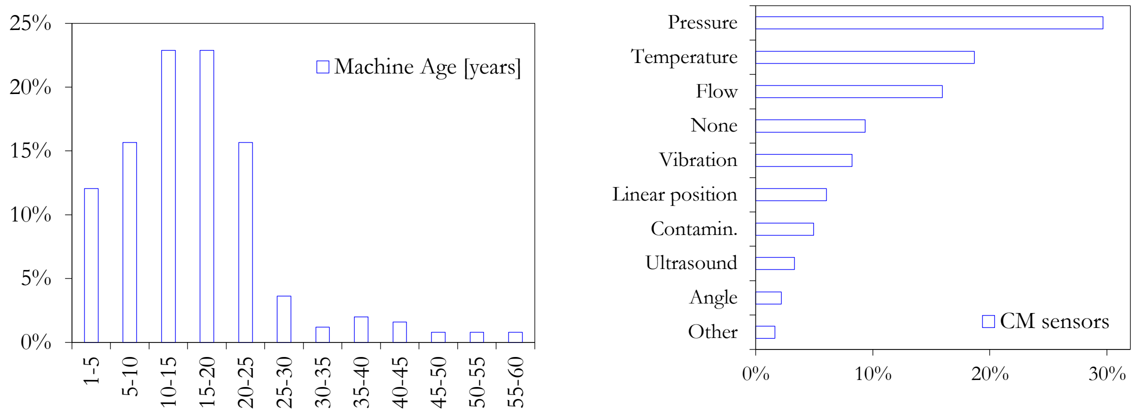


Figure 25. Maintenance practice (a) and available sensors (b) of respondents

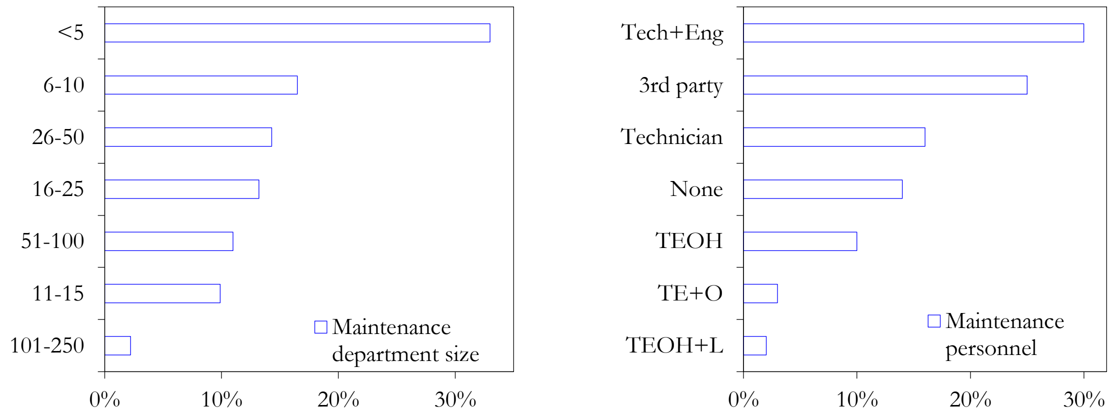
By far, the most important factor lacking in various studies (e.g. [119], [120]) is the machine age of the system or machine being investigated. This is extremely important in evaluating the hydraulic components and the state since the contaminant-induced wear, e.g. hydraulic pump, causes further contamination and degradation of different sensitive components. Suspecting that different machines and their associated frequency of failures (of components) is exponential (or Weibull), it is important to emphasise the machine state investigated in terms of the machine age. It can be seen that most of the machines are at a somewhat mid exploitation age state, presumably (Figure 26a). Earlier mentioned that machine state is monitored mostly on visual (regular) inspection intervals, the specified failure arrival is important to predict. Figure 26b shows that most companies rely on a machine's pressure, temperature, and flow state for optimising maintenance decision-making activities, which could be a beneficial argument for emphasising EBM practice.



(a) (b)

Figure 26. Machine age distribution (a) and machine state analysis program (b)

Going into the depth of the maintenance practice, it is important to see whether the department size (Figure 27) or maintenance personnel (Figure 27) influences or correlates with the MTBF indicator.



(a) (b)

Figure 27. Maintenance department size (a) and maintenance department team (b)

Data from an associated descriptive graph of maintenance department size suggests that up to 70% of the companies employ 0.15 to 0.25 maintenance personnel per machine (MPPM), i.e. one person is responsible for maintaining four machines at least (Figure 28a). On the other hand, Figure 28b shows that 30% of personnel are mostly technicians, while 25% are engineers. More worrying is that almost 15% rely on outsourced maintenance personnel, while only up to 5% are laboratorians and LCM experts. However, the "contradicting" factor is that companies who practice predictive analytics – trained personnel and sophisticated instruments – show excellent MTBF results, resulting in even fewer maintenance personnel per machine. These results impose questions: Does the maintenance quality in avoiding failures depend on the department team, personnel or technology? The evidence shows conflicting reasoning.

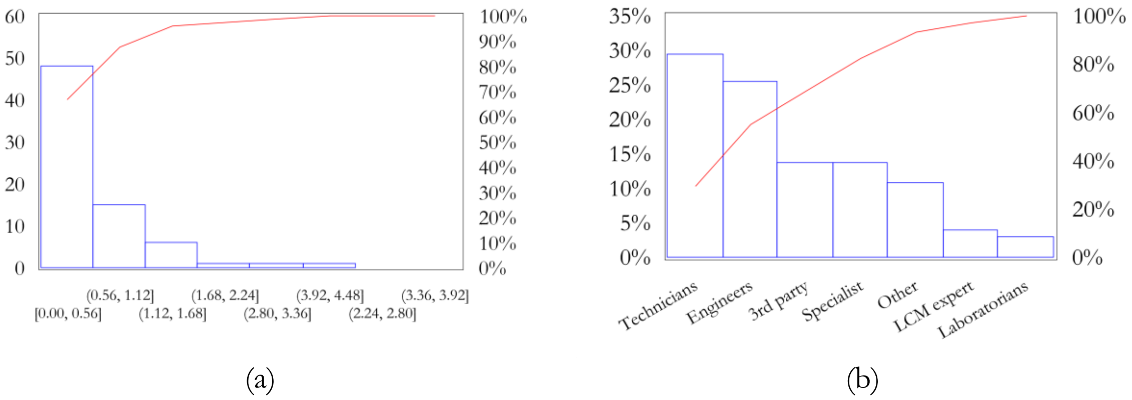


Figure 28. Maintenance personnel per machine (a) and failure analysis personnel (b)

Timely oil replacement is crucial for maintaining equipment reliability. Results show that most companies replace the oil at a reasonable time (Figure 29), while some do not replace the hydraulic oil even after 10k hours – questioning the oil quality and application workload. Most companies, however, rely on OEM suggestions without inspecting the oil quality.

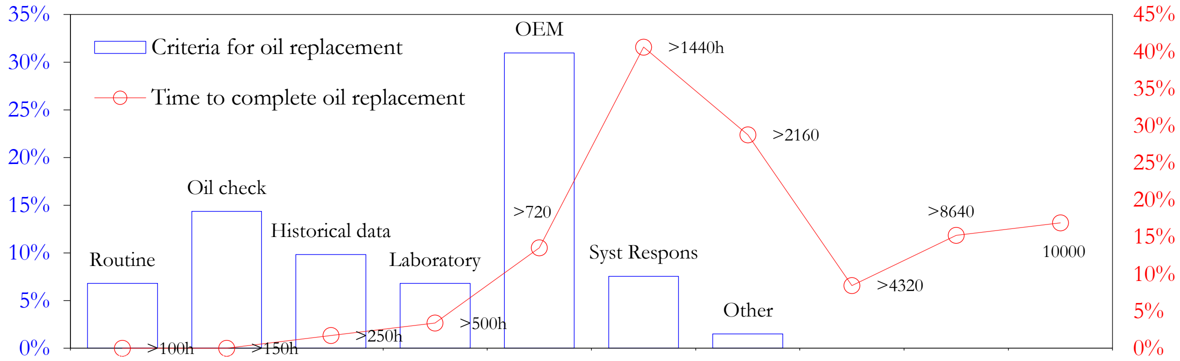


Figure 29. Criteria for oil replacement (y_1-axis) and time to complete oil change (y_2-axis)

Another important indicator of the maintenance practice' is filter replacement time (FRT) (Figure 30). Namely, adequately and timely replacement of filters significantly reduces wear-induced stoppages, particle ingression and clogging, thus reducing the risk of premature wear out of the system. If such practice or activities are performed, the inference is that FRT correlates with MTBF, suggesting that FRT contributes to preserving the system and prolongs TBF events.

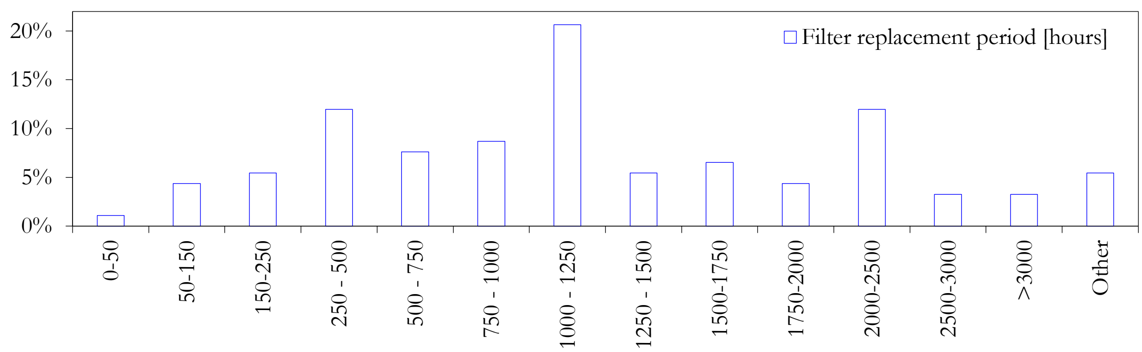


Figure 30. Percentage of companies obliging with proposed FRT reported

A good indication of the quality of the maintenance practice is the time for the oil refilling within the system (Figure 31). It has been observed that companies, to preserve the system and not replace oil with small degradation of oil constantly, usually refill the system after some time. Figure 31 shows that even though companies do not refill the system constantly, some peaks around 100h and 500h show a potential bias in oil analysis. Some data, therefore, may be prone to bias in terms of viscosity measurement after some time since oil is "refreshed" and returned to the appropriate state of viscosity quality level. Further analysis should be investigated, and potential degradation and particle rise in the system can cause bias in oil analysis.

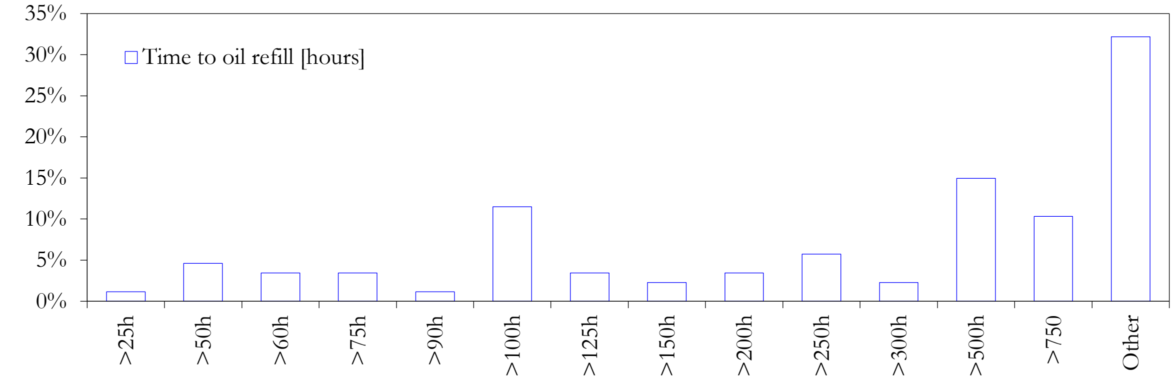


Figure 31. Time to refill the system with the oil

The variables above suggest that the analysis results can be biased when conducting the lubricant condition monitoring (LCM) program. These variables must be available and included in the final analysis and will be prone to the investigation later in the experiment.

5.1.3 MAINTENANCE PERFORMANCE INDICATORS DESCRIPTIVE RESEARCH RESULTS

Besides maintenance practice and associated activities (e.g. FRT, LCM), the performance indicators (e.g., MTBF, fluid waste, type and the root cause of failures) will be discussed further. Hence, looking at MTBF depicted in Figure 32, conclusions are difficult to be established. Therefore, multiple linear regression (MLR) will be used to investigate variables affecting MTBF.

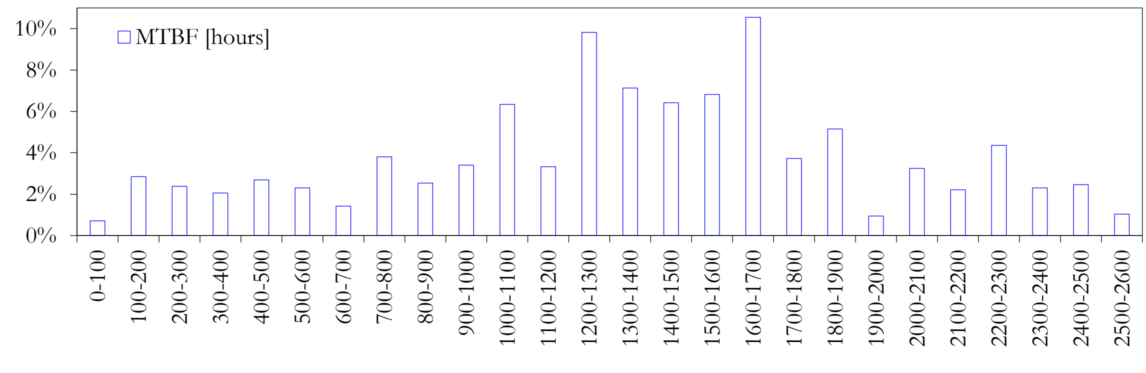


Figure 32. Mean Time Between Failures of industrial and mobile machines

Considering failures within the hydraulic system (Figure 33a) and their associated causes (Figure 33b), it can be seen that bursts of hoses and pipes are the most common stoppage within the hydraulic system, logically justifying the causes (or consequences) of the system overload and leakage. Outside of the spectrum of presumably inadequate operations leading to overload, contamination (particle, water, air, temperature) is the secondary cause of failures but not the most common cause of hydraulic system failure, as previously reported throughout the literature.

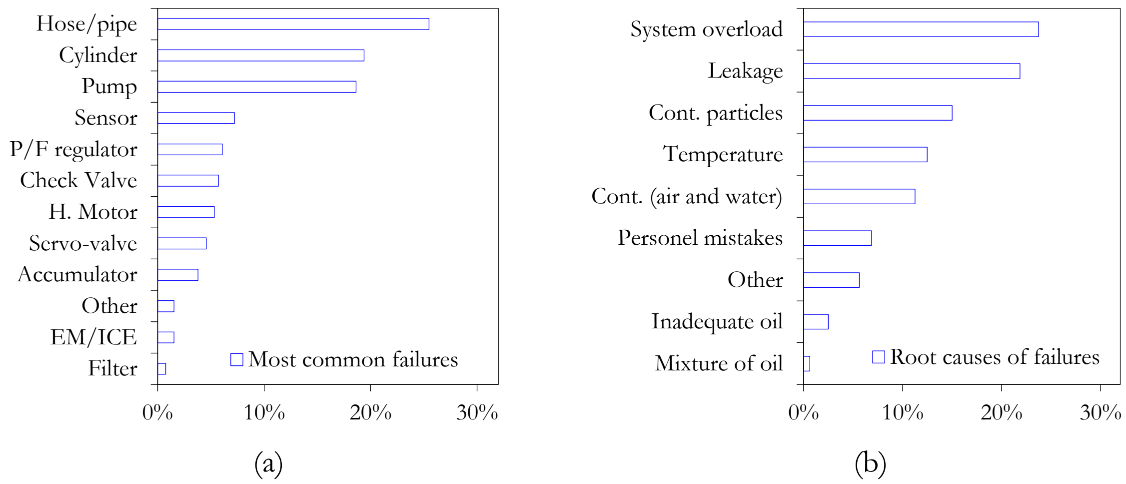


Figure 33. The most common component failures (a) and root causes of failures (b) reported

Although failures due to contamination (particle, temperature, air, water) are significantly lower than previously reported in the literature, it helps support the premise that future maintenance should switch focus on monitoring energy parameters, i.e. flow and leakage.

5.1.4 INFLUENCE OF ENERGY AND ENVIRONMENTAL INDICATORS

Obtaining data from the survey and associating it with appropriate maintenance practice (reported policy), the idea is to question the relationship between maintenance activities and MPIs. By obtaining evidence on the relationship between maintenance practice and MPIs (e.g., MTBF, energy, oil waste), the idea is to use such evidence for contributing to the EBM practice. Nevertheless, the first goal is to use box and whisker plots to illustrate the relationship between maintenance practices and MPIs, namely hydraulic power utilised (Figure 34a) and MTBF (Figure 34b).

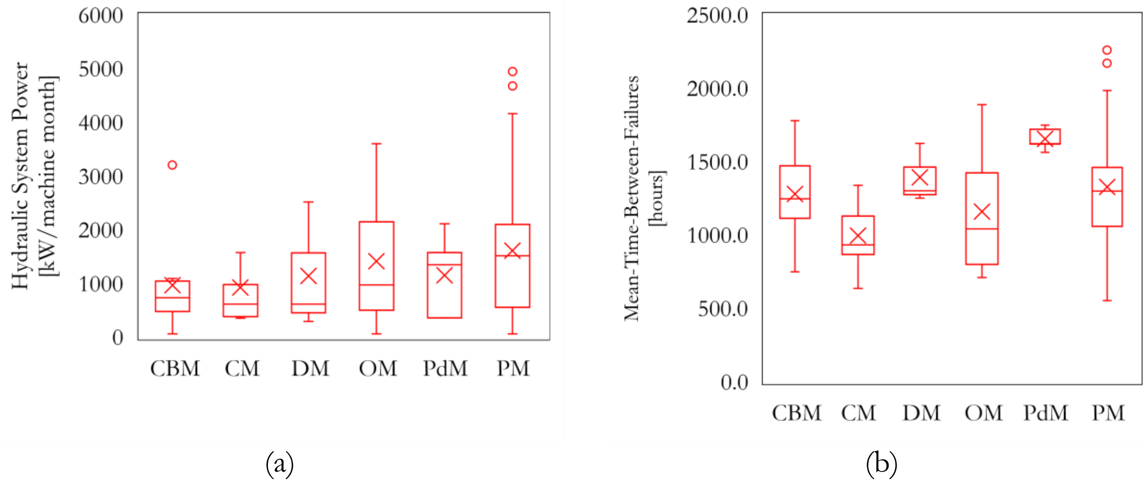


Figure 34. Box and whisker plot of PRCM (a) and MTBF (b) of different MP

The results depicted in Figure 34a show that power units (NWF and NWP) are at the lowest at CBM and CM practice; presumably, it can affect the MTBF indicator. However, the obtained results from Figure 34b shows that MTBF is somewhat close (mean and median) and should not bias results.

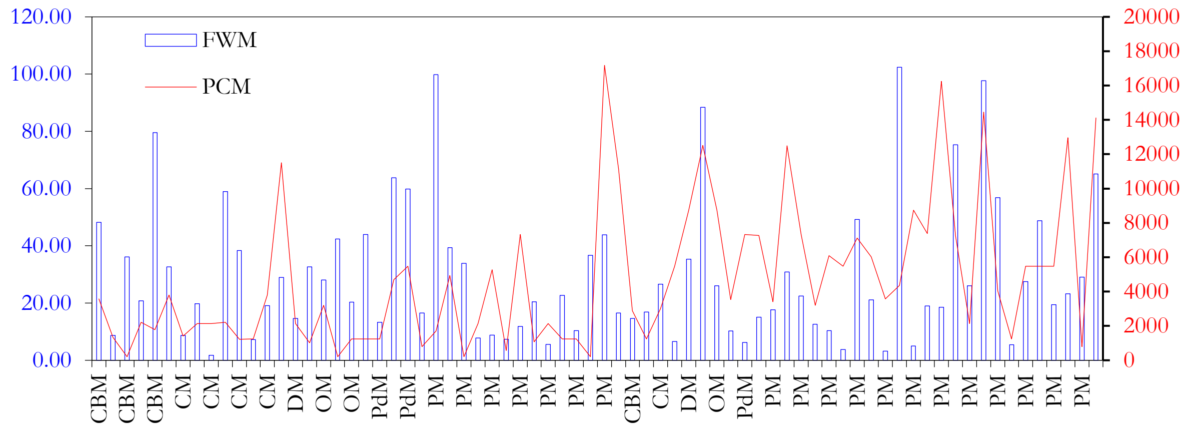


Figure 35. Companies utilising different MP fluid waste per machine month (y_1-axis) and power consumption per machine monthly (y_2-axis)

Furthermore, reported overload and leakage as primary causes of stoppages across the MPs do not correlate with fluid waste per month. On the contrary, in some small instances under CM practice, the higher the hydraulic power unit, the less it wastes fluid. A monthly scatter plot (Figure 36) of fluid waste and power consumption is used and subjected to MP to get closer to the proposed thematic. It can be seen that there is no correlation between observations. Therefore, although one may expect higher energy utilisation of hydraulic power units and information obtained – overload and leakage – that fluid waste monthly should result in a somewhat positive correlation between the variables. Although depicted in Figure 36, it shows the absence of such a correlation.

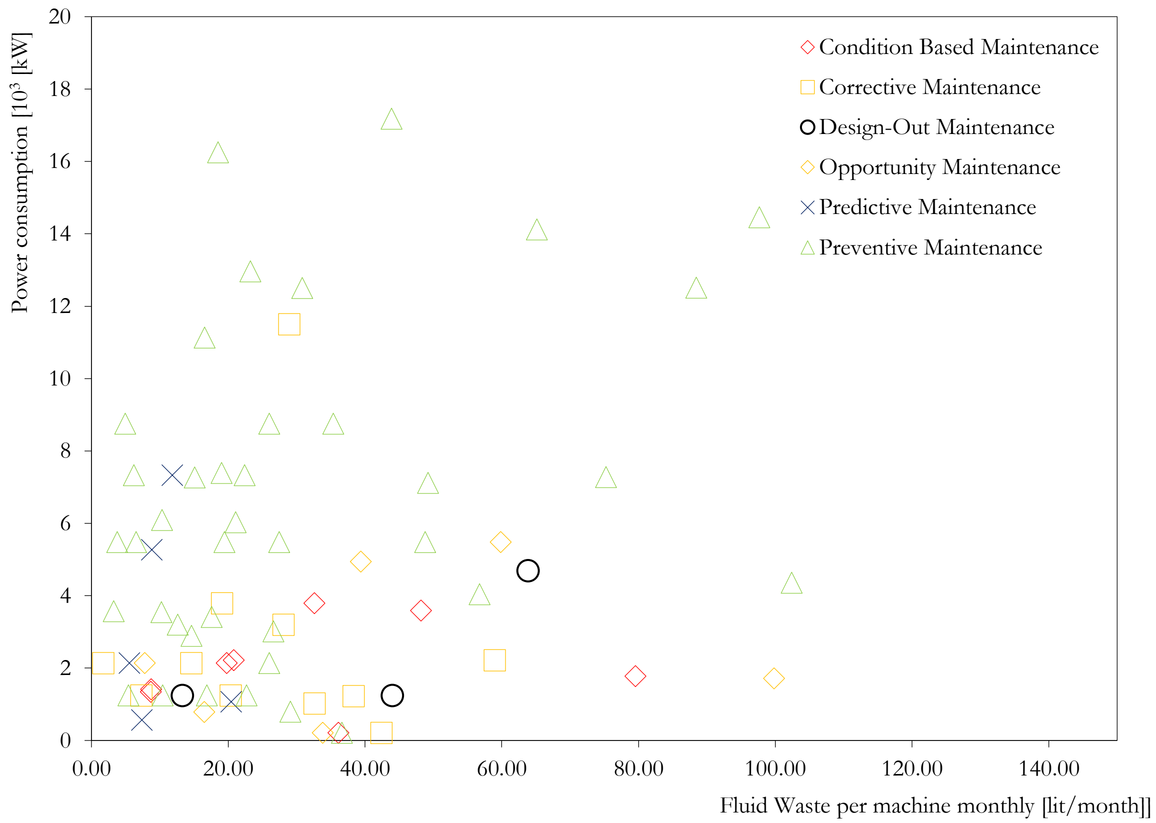


Figure 36. Scatter plot – PCM (y-axis) and FWMM (x-axis)

Investigating the influence between MTBF and fluid waste per machine-monthly (FWM) reveals that variables subjected to DM, CM, PdM, or PM do not correlate. However, CBM and OM practice shows that with higher and improved MTBF, FWM correlates. Namely, one of the reasons associated with activities for maintaining the system as operational as possible at the cost of allowing non-random deteriorating "quasi-failures", such as wear, to take charge. Other cases can include conducting conditional or opportunity maintenance inspections and acting upon deviations in machine performance (e.g., noise, temperature) with appropriate activities to reduce leakage or prevent overload, consequently preventing stoppages. Extreme cases would be, as stated earlier, to replace the oil based on degradation characteristics with results obtained from the lab. This case would be the most logical since it preserves the system in a good state and prevents degradation while maintaining the quality level of fluid. All of the reasons require in-depth analysis within specific monitoring practices; however, such data is beyond the scope of the study.

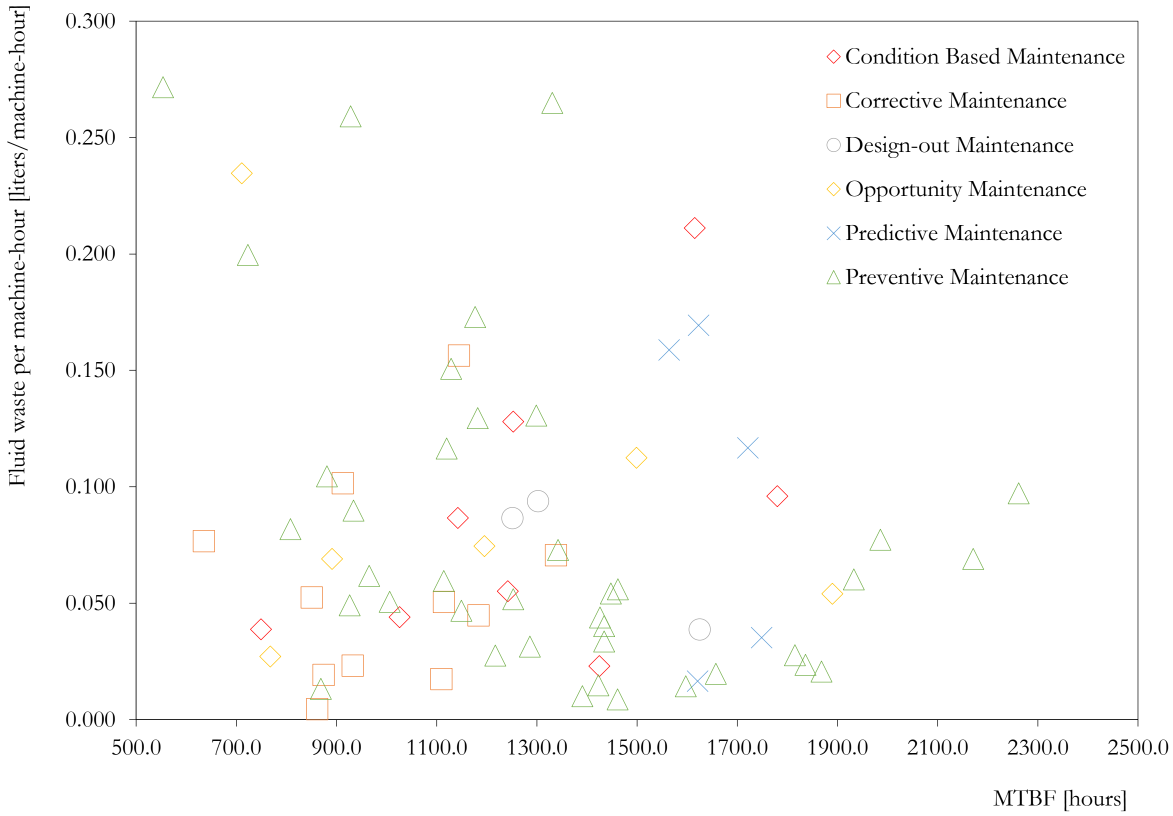


Figure 37. Scatter plot – FWMh (y-axis) and MTBF (x-axis) of different MP

Observing the scatterplot (Figure 38), the results show a negative correlation between MTBF and power consumption requirements of specific machines, i.e., hydraulic power units. Namely, it can be observed that regardless of the maintenance practice being subjected, most of the companies (machines within) show a higher MTBF with smaller power units expressed in kW. So, the argument goes to the importance of understanding the impact of pressure on flow on some failures reported. An objective viewpoint validating the importance of transitioning into the energy-dedicated maintenance realm further supports the previous argument. It can be observed that most of the power units above 40 kW of required power show stable MTBF varying around 700-900 hours. With a decrease below 40 kW hydraulic power unit, MTBF is clustered around 1300 hours (MTBF) regardless of the maintenance practice. Below 40 kW shows a negative exponential decrease towards higher MTBF, suggesting that smaller power units show exponentially reduced TBFs. Hence, this also questions other factors influencing MTBF, especially the high amount of required power machines. Since most industrial systems are at low power unit requirements, this also adds a validity dimension in accepting that the mobile machines with higher input power tend to fail faster, resulting in pipes and hoses bursting, leakages and exposure to harsh working environments. It also supports monitoring this type of indication for preventive maintenance inspection periods.

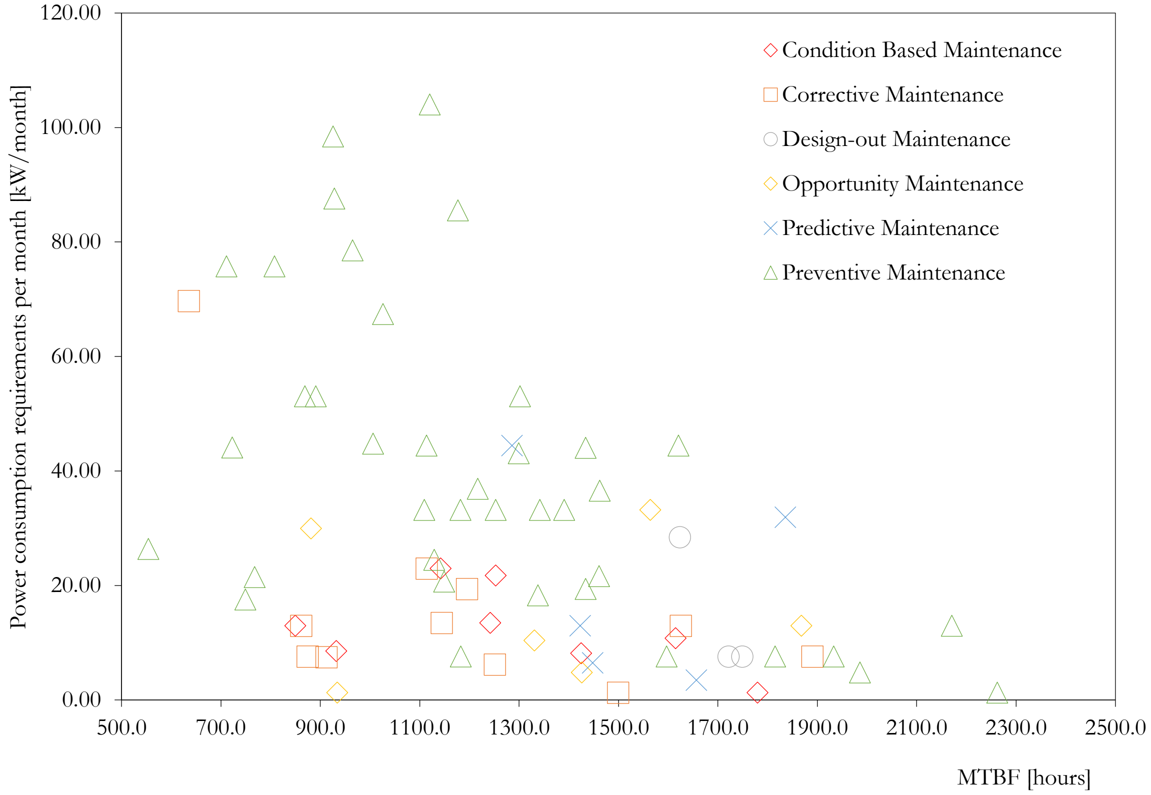


Figure 38. Scatter plot – Power unit [lit./machine-hour] and MTBF [hours]

The information collected regarding PCM, FWM and MTBF variables leads to the following conclusion. Even though MTBF shows, a low to mild correlation (tendency) with the previous two variables, the correlation between PCM and FWM is absent. Since it has been reported that both overload and leakage are the primary causes of failures, the observed data supports such a claim. Namely, different latent indicators and causes of failure between different industrial applications and machines lead to different types of failures (e.g., constructional or functional); the presence between MTBF and PCM cannot be confirmed by deductive reasoning. This hypothesis needs to be challenged by inductive reasoning and classifying different root causes of failures – further supporting the premise of the causality between functional-productiveness markers and faulty operating conditions to reach the machine's operating state.

5.2 CORRELATION AND REGRESSION ANALYSIS OF SURVEY DATA

5.2.1 CONTAMINATION – THE PRIMARY CAUSE OF STOPPAGES?

The first hypothesis from state-of-the-practice is to challenge the argument that contamination (>70%) is the lead cause of failures within the hydraulic systems. One may conclude that there is a strong correlation then between wear-induced mechanisms of leakage and consequently question the true cause of the stoppage. Therefore, the Z test shows the following results:

$$z = \frac{\hat{p}-p}{\sqrt{\frac{p \cdot q}{n}}} = \frac{0.39-0.7}{\sqrt{\frac{0.7 \cdot 0.3}{72}}} = -5.75. \tag{5.1}$$

Following previous claims [121] regarding the influence between failures and, thus, associated maintenance activities of filter replacement time (FRT) that must have a negative correlation or positively influence a reduction in MTBF, the results support such claim. Although the maintenance analysis program (MAP) and maintenance department team (MDT) do not show a correlation affecting MTBF, they will be further investigated.

Table 13. Correlation matrix – MTBF and associated maintenance variables

	MA	*NWP*	*NWF*	*MPPM*	*MDT*	*MAP*	*FAP*	*CMT*	*FRT*	*TTOR*
NWP	-0.01									
NWF	-0.05	0.45***								
MPPM	-0.12	0.20*	-0.07							
MDT	-0.18	0.13	-0.11	-0.06						
MAP	-0.11	-0.02	0.03	0.22*	0.06					
FAP	-0.14	-0.08	0.03	0.04	0.40***	0.13				
CMT	0.03	0.09	0.02	0.1	0.02	0.5***	0.07			
FRT	0.04	0.1	0.06	-0.1	0.06	-0.14	-0.22*	-0.18*		
TTOR	-0.12	-0.14	-0.06	-0.22*	0.25*	0.20*	0.01	-0.11	0.1	
TTCOC	-0.02	-0.03	-0.11	-0.04	0.25*	0.25*	-0.09	-0.1	0.1	0.6***
MTBF	-0.38***	-0.50***	-0.33***	0.02	0.14	0.07	0.23*	0.25**	-0.4***	0.1

NOTE: MTBF = Mean Time Between Failures; MP = Maintenance Policy; MAP = Maintenance Analysis Program; MPPM = Maintenance Personnel Per Machine; MDT = Maintenance Department Team; FAP = Failure Analysis Personnel; MA = Machine Age; FRT = Filter Replacement Time; CMT = Condition Monitoring Technology; TTOR = Time To Oil Replacement; TTCOC = Time To Complete Oil Change;. p-value < .01***, p-value < .05**; p-value < .1*

Displayed results show a low p-value of MA, NWP, NWF, FRT, FAP, CMT, and after running a Stepwise Multiple Regression (SMR) in MINITAB and using ANOVA, the coefficients show the $p > 0.05$ and are excluded from the modelling. Besides, a Grubbs test ($G = 2.77$) showed no outliers ($p < 0.05$), and a scatter plot was used to check linearity.

The second assumption is to check multivariate normality, i.e. errors of observed and predicted values are normally distributed (Figure 39). The third assumption is to check the absence of multicollinearity, proven with no coefficients between independent variables $r > 0.80$. The final proposition for validating the regression model is to check the presence of heteroscedasticity in the data, and the model's linearity suggests homoscedasticity (Figure 39).

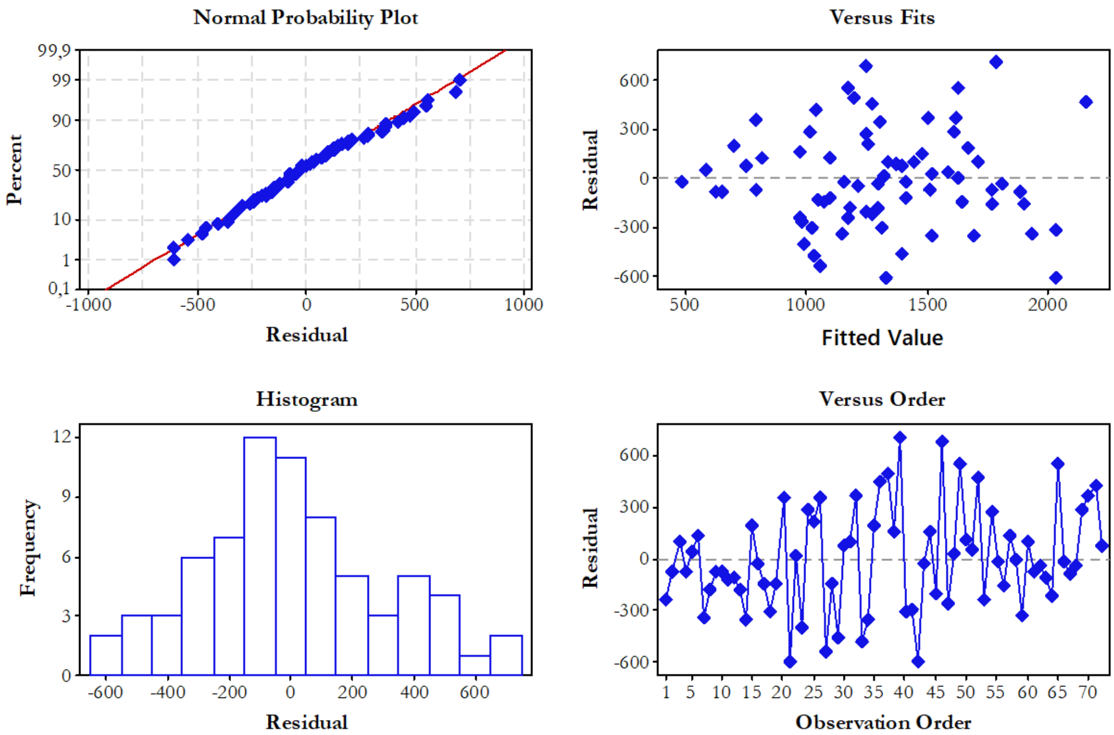


Figure 39. Residual plot analysis for MTBF

Confirming the linearity assumption, a general MLR analysis model is formulated as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon\,, \tag{5.2}$$

Where y is an independent variable, β_0 is the intercept, β_i are coefficients, x_i is the associated dependent variable with error $\varepsilon \sim N(\mu, \sigma^2)$. Replacing with MTBF model target function, we get:

$$MTBF = 1224 - 0.079\,FRT - 0.76\,MA + 0.443\,TTOR - 1.578\,NWP - 1.063\,NWF + MP + MAP + FAP + CMT\,. \tag{5.3}$$

Since categorical variables like MP, MAP, FAP and CMT are used, dummy values are used for modelling (0, 1). The resulting model shows somewhat average prediction properties of $R^2 = 60\%$.

Table 14. Resulting R^2 values for the proposed MTBF linear function model

Model	***S***	***R^2***	***R^2_{adj}***
MTBF	348.487	60.61%	46.22%

Although the model with intercept shows a somewhat moderate R^2 value, the amount of accuracy of extracted data from the survey is questionable. Namely, some variables consisting of dummy values (MP, MAP, FAP) fail to prove the validity considering p-value.

5.2.2 Model and coefficients influence and validity

ANOVA results (Table 15) show that most associated variables show p values less than 0.05. However, although variables such as MP, FAP and NWF in both proposed models deviate from the value, the inference is that a correlation exists between MTBF and mentioned. However, since the model does not have good prediction properties with associated variables, thus reducing the R^2 value (in the first case), the model illustrates the impact of variables that show good correlation r values with the dependent variable MTBF. Looking at the categorical variables of the MP influence, there is not enough evidence to reject the claim that MP increases MTBF. Even though the logical inference that practices like CBM and PdM should increase MTBF, which the model confirms, the *p*-value does not reject the null.

Table 15. ANOVA results of coefficients used in the MLR models

Source	***df***	***Adj SS***	***Adj MS***	***F value***	***p-value***
Regression	19	9718237	511486	4.21	0.00
FRT	1	136746	136746	1.13	0.29
MA	1	2765909	2765909	22.78	0.00
TTOR	1	380276	380276	3.13	0.08
NWP	1	1033465	1033465	8.51	0.00
NWF	1	257000	257000	2.12	0.15
MP	5	358924	71785	0.59	0.71
MAP	3	1149065	383022	3.15	0.03
FAP	3	115429	38476	0.32	0.81
CMT	3	6315047	121443	6.35	0.00
Error	52	2312777	770926		
Total	71	16033284			

Table 16 shows that FAP improves MTBF, although the discrepancy and somewhat contradictory claim that technicians outperform engineers in determining failure is questionable, in addition to non-significant statistical relationship ($p>0.05$). It should be investigated to see whether or not experience and not education contributes to diagnostics and prognostics, in which case, it can be justifiable. Finally, a CMT with a statistically significant value at $p<0.05$ shows that personnel using sophisticated technology increase MTBF value, whereas organisations that lack instruments (e.g., pressure, flow, temperature, contamination sensors) decrease MTBF.

Table 16. MTBF for continuous and categorical coefficients

Term	***Coeff***	***SE Coeff***	***T value***	***p value***	***VIF***
Constant	1224	463	2.64	0.011	
FRT	-0.079	0.0744	1.06	0.294	1.79
MA	-78.6	16.5	-4.77	0.000	1.19
TTOR	0.443	0.250	1.77	0.083	1.25
NWP	-1.578	0.541	-2.92	0.005	1.36
NWF	-1.063	0.731	-1.45	0.002	1.31
MP					
CBM	0	0	*	*	*
CM	-285	220	-1.30	0.199	3.7
DM	7	295	0.02	0.981	2.06
OM	-154	252	-0.61	0.544	2.88
PdM	60	206	0.29	0.771	1.63
PM	-115	185	-0.62	0.537	5.01
MAP					
CC	0	0	*	*	*
LCM	529	204	2.59	0.013	2.45
PHM	-23	193	-0.12	0.906	4.68
Visual	248	163	1.52	0.134	3.93
FAP					
Engineer	0	0	*	*	*
None	98	154	0.64	0.528	2.19
Specialist	49	112	0.43	0.667	1.86
Technician	146	162	0.9	0.370	1.53
CMT					
None	0	0	*	*	*
PF	760	325	2.34	0.023	14.67
PFT	695	363	1.92	0.061	15.66
PFTC	1206	366	3.30	0.002	17.26

However, what is questionable is the Variance Inflation Factor that (rule of thumb VIF < 10) influences multiple collinearities, i.e., FAP and MAP are correlated with the CMT and can be left from the model. As such, it can be seen that the LCM analysis program significantly outperforms other maintenance programs for improving the time between failures due to the usage of sensor and lubricant condition technology.

Although maintenance programs are mostly investigated in the research domain of maintenance, it still lacks an industry-accepted approach and methodology as means of technical and technological intelligence of engineers in determining degradation and failure patterns. It shows a high *p*-value, which cannot be used to determine the validity of using a binary variable [0, 1] in model validity. Perhaps companies using the PHM approach fail to address and implement the appropriate methodology, resulting in inadequate failure analysis. In addition, let's use only the statistically significant factors in model, which is given as follows:

$$MTBF = 1557 - 78.0\ MA - 1.607NWP - 1.155\ NWF + CMT\ , \tag{5.4}$$

where CMT considers constants (766 in case of PF, 819 in case of PFT and 1106 in case of PFTC), suggesting that the best condition monitoring is in fact monitoring the pressure, flow, temperature and contamination in the system since it prolongs the MTBF by 1106 hours (Table 17).

Table 17. MTBF for continuous and categorical coefficients

Term	***Coeff***	***SE Coeff***	***T value***	***p value***	***VIF***
Constant	1557	294	5.36	0.000	
MA	-78.0	15.8	-4.95	0.000	1.01
NWP	-1.607	0.512	-3.14	0.003	1.13
NWF	-1.155	0.700	-1.65	0.104	1.12
CMT					
PF	766	268	2.85	0.006	9.33
PFT	819	272	3.01	0.004	8.20
PFTC	1106	270	4.09	0.000	8.76

The model, however, does not perform vey well, which can also be noted by the results given in Table 18. In addition, the question have also rised on the NWF variable in terms of model contribution, since it does not have statistically singnificant effect on the model (p = 0.104), and should also be removed from the model.

Table 18. Resulting R^2 values for the proposed MTBF linear function model

Model	***S***	***R^2***	***R^2_{adj}***
MTBF	361.013	47.16%	42.29%

Overall, it can also suggest that industrial maintenance practitioners lack knowledge on the usage of such technology, or other factors can impede the data. Such factors include personnel mistakes, higher power units, available maintenance personnel per machine (MPPM) for conducting the analysis, influence of hard-working environments, or appropriate usage of instruments. Either way, the question remains open and should be a groundwork for further discussion and investigation.

Chapter III

„...mass men lead lives of quiet desperation.“

Henry David Thoreau

6 EXPERIMENTAL SETUP

Considering all acquired information, the domain in which the model needs to be verified must provide a high energy-utilisation process within the manufacturing domain. Justifying the proposed model reduces resource consumption, pollution, and financial loss. Moreover, for EBM to be effective, a new model must be proposed to estimate quasi-failure states as binary values [0, 1] as normal and faulty-mode states. The classification learning problem is used for dynamic changing boundaries and clusters. Since we are dealing with both discrete and continuous values, the following sub-sections will first deal with testing does the contamination, in fact, influences, directly or indirectly, energy consumption and if the value represents multicollinearity and redundancy of EBM markers. The idea is to create functional-productiveness markers for performing classification.

6.1 INDUSTRIAL PRACTICE DATA AND MACHINE SELECTION

6.1.1 WORKING CONDITIONS AND CHARACTERISTICS FROM PRACTICE

State-of-the-practice meta-data is used to assess experimental validation of the proposed model through a similar system. That is to say, all variables taken from practical environments are encapsulated in such a way that they are suitable for experimenting. The underlying reason is to subject the system to disturbances and perturbations that are dealt with in real operating conditions – verifying the model in an industrial encirclement. Table 19 provides descriptive statistics of questionnaire-based survey meta-results. As observed, Table 19, which includes industrial applications, shows a mid to average range of working conditions, hence, hydraulic power units of around 17 kW, while mobile machines are more than two times higher working loads with power units ranging above 40 kW. This suggests that this feature shows the higher intensity of variations in reducing MTBF, aside from all other factors included.

Table 19. Industrial machines utilising hydraulic control systems - descriptive statistics

Variable	*mean*	*median*	*st. dev*	*kurtosis*	*skewness*	*min*	*max*	*A**	*p-value*
FRT	817.53	742.50	406.3	1.57	1.17	200	2000	1.15	<0.005
FWMh	0.123	0.094	0.092	1.76	1.26	0.007	0.4159	1.02	0.010
MA	9.34	8.80	2.09	-0.95	0.12	5.6	13.3	0.51	0.187
MFV	385.30	175	517.87	3.11	2.04	53	2000	5.32	<0.005
MPPM	0.68	0.3	0.845	6.58	2.43	0.04	3.93	3.69	<0.005
MTBF	1381.5	1423.0	382.9	-0.66	0.09	635	2262	0.32	0.516
NWF	52.3	38	32.74	.020	0.91	10	130.5	1.68	<0.005
NWP	145.21	114.33	84.2	14.73	3.26	65	550.5	3.00	<0.005
PCM	17.20	10.75	20.07	9.99	2.90	1.26	104.02	3.71	<0.005
TTCOC	2672.4	1800	2147.2	2.67	1.76	620	8640	3.63	<0.005
TTOR	166.80	91	171.04	3.47	1.91	250	739	3.46	<0.005

NOTE: MA = Machine Age; NWP = Nominal Working Pressure; NWF = Nominal Working Flow; FRT = Filter Replacement Time; MFV = Machine Fluid Volume; TTOR = Time To Oil Refilling; TTCOC = Time To Complete Oil Change;. MTBF = Mean Time Between Failures; FWMh = Fluid Waste per Machine-hour; PCM = Power Consumed (required) Machine – hydraulic power unit; MPPM = Maintenance Personnel Per Machine; **A*** = Anderson-Darling normality test score.

6.1.2 EXPERIMENTAL SETUP – RUBBER MIXING MACHINE (RMM)

Considering that companies' most important goal is to achieve the finest market quality of their products, improving process control is important. Such an approach requires that the process (regardless of the decision-making layer) from raw material to the final product (even service) maintains a defined quality level. From a technical/technological stance, the point of characterisation and discussion will focus only on a specific production process utilising a hydraulic control system. One such system is a rubber mixing machine (Figure 40). Although the process consists of multiple stages from transformation into a final product (tyre), the only part of the experimental design and monitoring system will be disposing of rubber on the roller line by opening and closing the mixer saddle. The working system consists of a tank (1), EC motor (2), axial piston pump (3), manifold block with directional-control valves (4) and hydraulic actuators (5). The monitoring apparatus for data acquisition consists of instruments with sensors and data transformation units consisting of: (6) water sensor for measuring water saturation; (7) contamination sensor for measuring particle contamination; (8) turbine flow meter for measuring working flow and pressure; (9) data acquisition instrument for flow and pressure; (10) communication module; (11) laptop; (12) SCADA system.

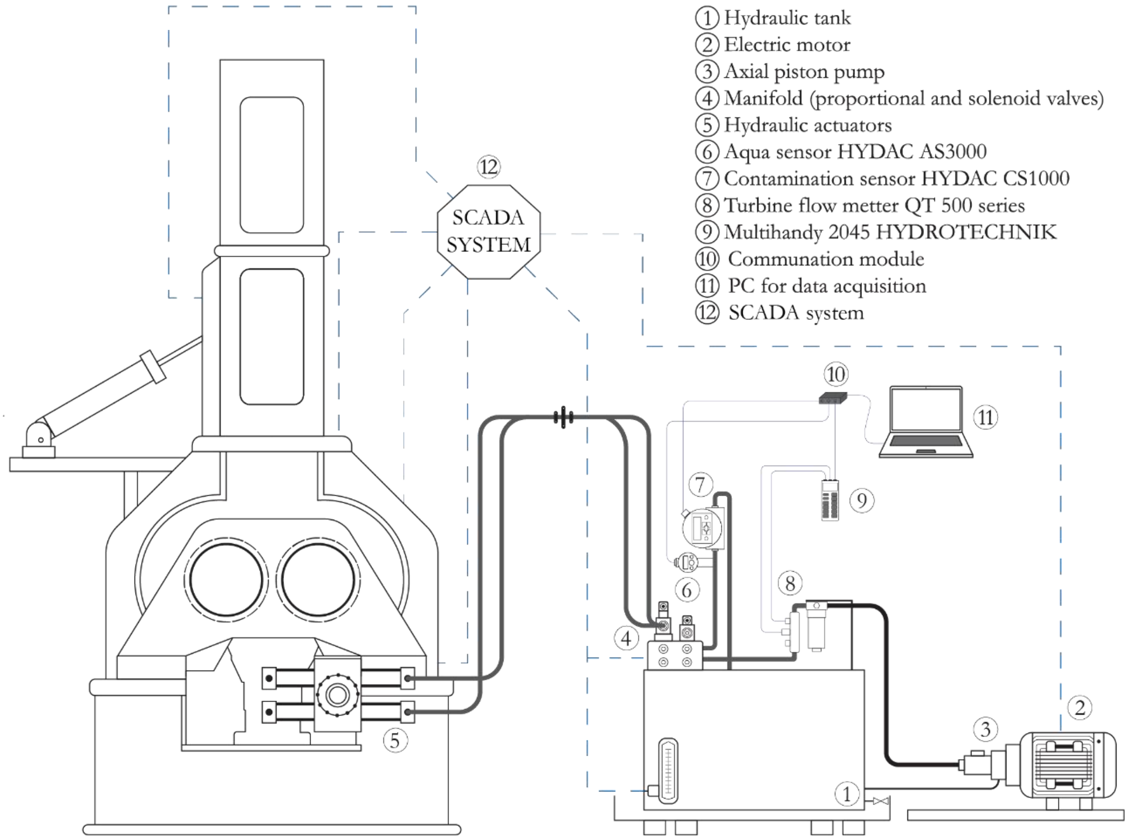


Figure 40. Experimental installation of the rubber mixing machine

Depending on the technological recipe for manufacturing a tyre, i.e. transformation from the process mass through mixing into a final product, i.e. tyre, an example of a specific work process flow is given as a technological fingerprint of energy consumption for a rubber mixer (Figure 41). The steps of mixing the mass for a specific batch starts includes (1) loading (feed); (2) soot filling; (3) mixing with batt; (4) ventilation; (5) mixing with batt with an increasing percentage of pressure; (6) oil filling; (7) again mixing with batt pressure; (8) release of batt pressure and retraction in addition to ventilation; and finally, (9) release of the mass for the next operation by opening and closing the saddle via the hydraulic control system.

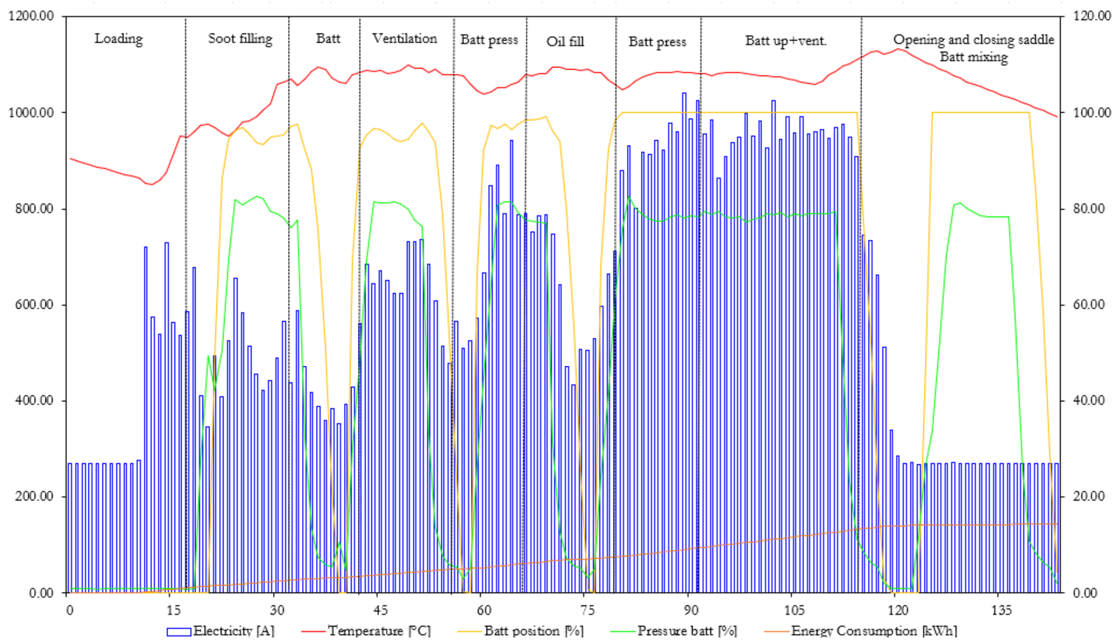


Figure 41. Energy consumption and act step of a rubber mixing process

Figure 41 shows that energy consumption is the highest at the start of the hydraulic control system that controls the opening and closing of the saddle door. The specific operation is triggered by the temperature set at a specific value. Moreover, the graph depicts the energy consumption of electric motors (rotor speed and moment) required for the mixing process. These controllable parameters include rotor speed, mixing time, ram pressure, and chamber temperature.

6.2 THE HYDRAULIC CONTROL SYSTEM OF RMM

The mixer's defined chamber temperature (inner temperature) is the point of the hydraulic system's starting process (and monitoring). The following subsection will be given a complete hydraulic installation (Figure 42) and step diagram (Figure 43) to fully understand the hydraulic system operation. The components of a hydraulic installation are given in Table 20.

Table 20. Hydraulic system components of a rubber mixing machine

n	*Component*	*Type*	*Characteristics/function*
1.	Reservoir	Hydraulic tank	200-litre hydraulic reservoir
2.	Filter	Suction filter at the pump	90-micron suction filter
3.	Pump	Variable displacement axial piston	46 cm^3/rev size axial pump
4.	Electromotor	Three phase electric motor	18.5 kW electric motor
5.	Valve_05	Pump displacement reg.-valve	Regulating swash plate angle
6.	Valve_06	Solenoid 2-position valve	Idle-working system valve
7.	Valve_07	Non-return valve	Valve for securing return pressure
8.	Multihandy 2045	Pressure and flow sensor	Monitoring working flow and pressure
9.	Filter	Pressure filter	10-micron pressure filter
10.	Directional valve	4/3 solenoid valve	Controlling actuators' position
11.	Directional valve	4/3 Proportional directional valve	Flow control to the actuator
12.	Flow regulators	Flow regulating valves	Controlling the saddle
13.	Actuators	Rock & pinion cylinder	Controlling the position of the saddle
14.	Contamination sensors	Particle and water sensors	Monitoring water sat. and particles

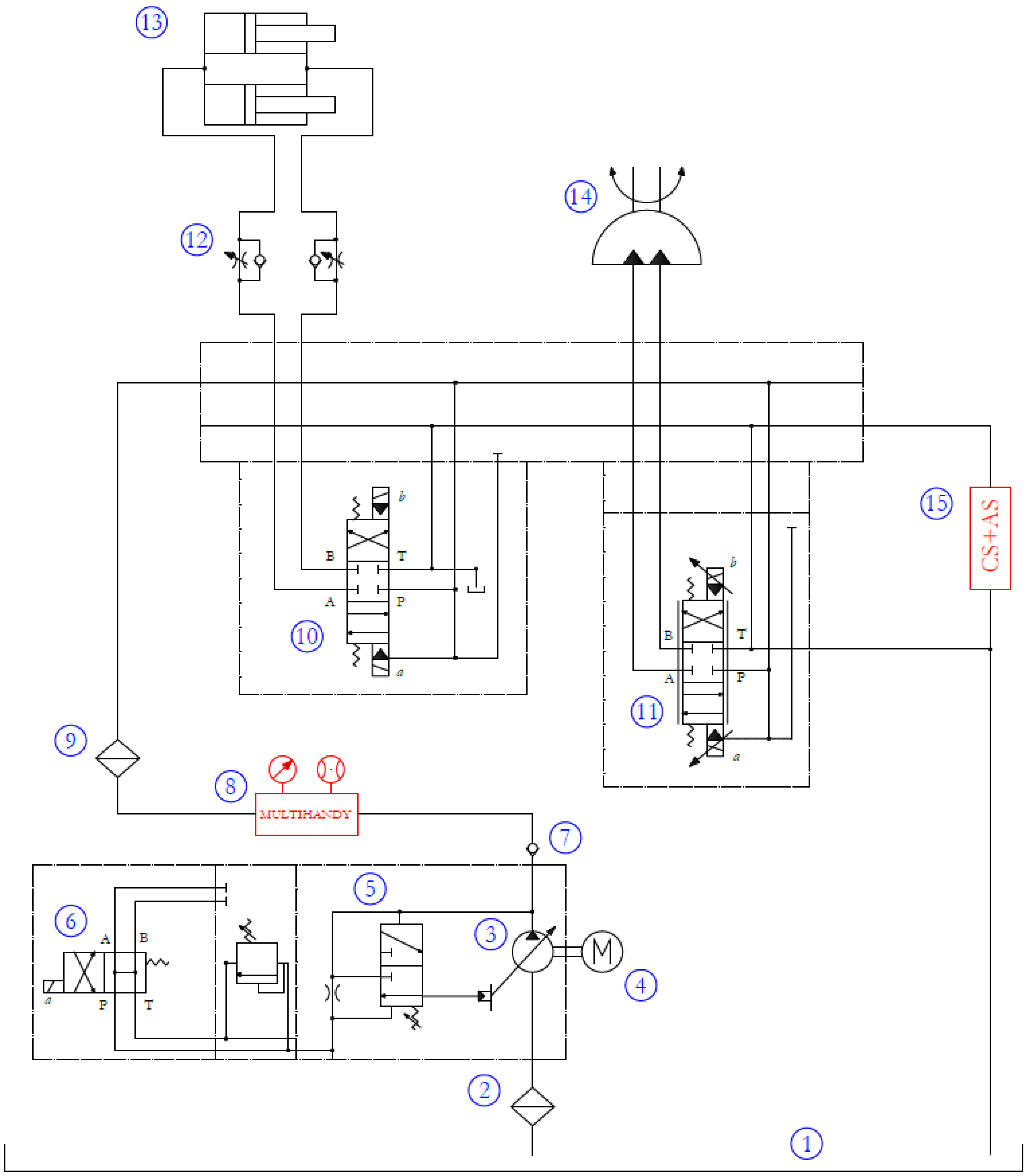


Figure 42. Hydraulic scheme for rubber mixing machine for opening and closing the saddle

The system works based on the following. In the idle (pre-start) phase, the pump is working at low pressure before the temperature sensor triggers the regulation valve of the pump (6) for starting the hydraulic cycle. After the initiation of the pressure rise solenoid valve (10) is activated, and the flow is transferred to cylinders (13). The cylinders are returned from the fully opened position to the fully closed. Immediately after cylinders (13) retraction, the Rack and pinion cylinder (14) are activated over the proportional valve (11). The saddle speed is regulated by fast movement in the first 2 seconds and slowed down approximately 2.5 seconds. This is the opening saddle (OS) position. Before the position sensor activates the proportional valve, the approximate time is around 8 seconds. This is the idle saddle (IS) position and is used to allow the process mass of the rubber to be ejected from the mixer. The closing saddle (CS) regime is performed the same way as it was a regime in closing. The rack and pinion cylinder (13) return the saddle to the primary position, and linear cylinders (11) act as a saddle's security door.

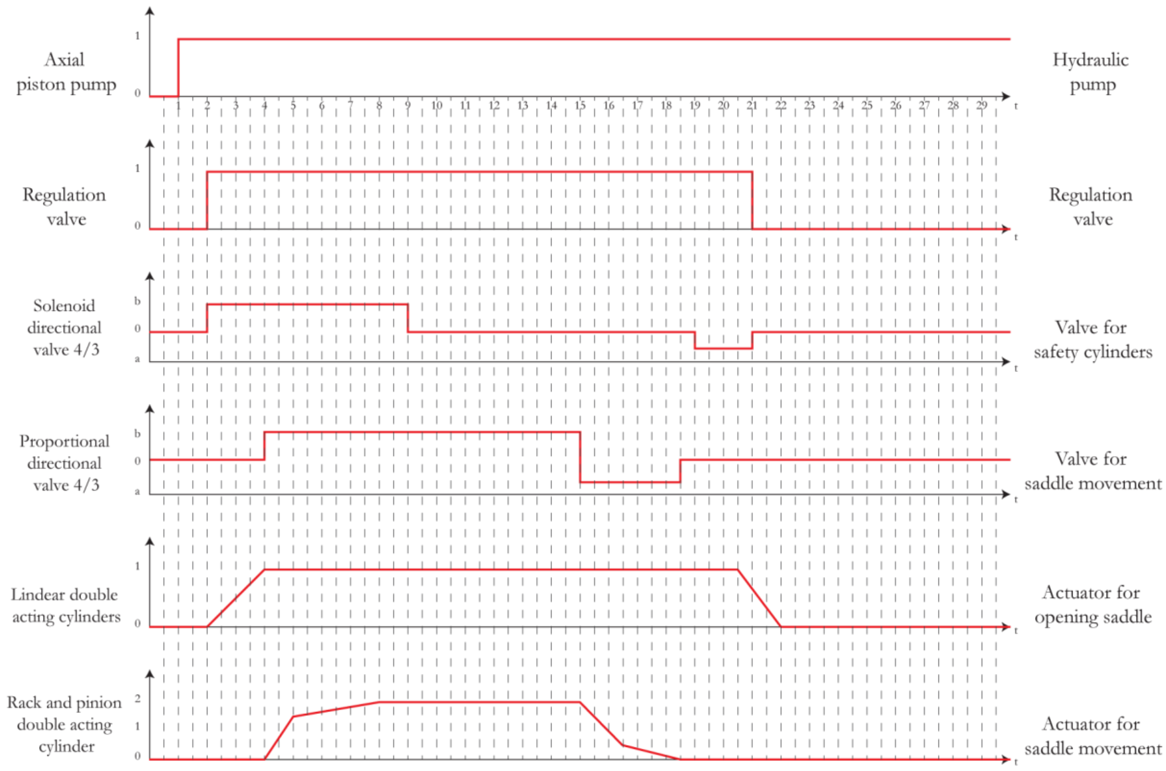


Figure 43. Work tact of the experimental hydraulic system

6.2.1 LUBRICANT CONDITION MONITORING DATA – HYDRAULIC FLUID

The fluid's primary function in the hydraulic system is transferring forces and motion, i.e., transferring power. Besides, hydraulic fluid is also responsible for lubricating the components', behaving as heat medium, sealing medium, antiwear and antioxidant medium. Considering the system's reliability and energy-conserving properties, it is crucial to select fluids based on the working conditions properly (e.g., working pressure, environment temperature, working regime). Depending on the features (e.g., EP-AW additives, resistance to ageing, thermal stability, viscosity, water mixing ability), oil with proper characteristics must be selected to sustain the required demands. As suggested by the OEM for the specific machine used in the experiment, HLP 46 hydraulic fluid is used. The HLP 46 is a conventional hydraulic mineral fluid with anti-wear additives meeting DIN 51524 part 2 standard requirements and ISO viscosity grade, and as such will be used for analysis by online (instruments) and offline (sampling) monitoring.

Table 21. HLP 46 fluid characteristics from OEM

Properties	***Standard***	***Unit***	***Value***
Colour	ASTM D 1500	-	1.5
Kinematic viscosity 40°C	ASTM D 445	mm^2/s	46
Kinematic viscosity 100°C	ASTM D 445	mm^2/s	97
Viscosity index	ASTM D 2270	-	97
Total acid number	ASTM D 664	mg KOH/g	0.8
Pour point	ASTM D 5949	°C	-30
Specific gravity @ 15.6 °C	ASTM D 4052	g/cm^3	0.878
Flash point	ASTM 92	°C	227

The first goal of extracting oil samples from the system is to maximize the information density [122], i.e. ensure that samples taken have as much information per millilitre of fluid as possible. The second goal is to minimize data error as much as possible by guaranteeing no bias in the fluid sample analysis. Oil sampling on system returns includes procedures dependent on system design, ports, pipes and hoses, application, conditions, and work regime. However, with high consistency, it can be said that turbulent areas are the best sampling locations because fluid is not at a laminar flow regime, thus avoiding the error of particle swarm leaving the sample (fly-by) – samples taken at elbows. Ingression points should be taken downstream of the components that wear and away from areas where particles and moisture ingress – returning and drain lines. Hence, oil samples are taken at return lines before filtration points (Figure 42). According to defined labelling and information collected from the sampling, a specific procedure and table of important information are given for gaining more insight after hydraulic fluid analysis. Every sample is recorded and analysed.

Table 22. Hydraulic fluid samples labelling and data explanation

Label	Properties	Explanation of the property defined
Fluid type	Fluid base type	Hydraulic fluid
Manufacturer	Fluid manufacturer	Original hydraulic fluid manufacturer
Fluid system	Machine or system name	e.g. Rubber mixing machine
Sample date	Sampling date and time	Exact time and date of sampling
Sampling hours	Hours before the last sample period	Hours before the last sampling
Sampling op. hours	Operating hours before the last sampling	Operating hours before the last sample
Disturbances	Fluid added before the last sample?	Amount of fluid added after the last sample
Sampling type	Offline, online or inline?	Type of fluid extraction from the system
Place of sample	Place where the fluid is sampled?	Barrel, tank, pump, valve, drainage, etc.
Sampling method	A ball and sample valve, vacuum pump?	Type of fluid sampling from the system
Sample amount	Amount of fluid taken?	Amount of fluid taken in ml or bottle size

Data is collected from oil samples by two offline laboratory analyses. Namely, the data collected is done as a double test to ensure data reliability. For instance, viscosity at 40°C and 100°C are analysed in two different laboratories to ensure data is valid through a single-blind study – not providing previous information about the fluid characteristics nor the fluid sample property to the laboratorian. Although not previously done, the author wanted to ensure a limited amount of bias in oil analysis.

6.2.2 FLUID SAMPLING AND ANALYSIS OF FLUID PROPERTIES

Hydraulic fluid sampling is usually done between 250-400 hours [54], [123], [124], depending on the application. The exact values of sampling are given in Table 23. Collected fluid samples are additionally sent to laboratories for analysis to avoid bias and non-replicable results. The information regarding the samples, protocol, method, instrument and overall analysis results are given in Appendix 2. In addition, laboratory elemental analysis is performed via Wavelength Dispersive X-ray Fluorescence (WDXRF) spectroscopy.

Table 23. Fluid sampling frequency with amounts and sampling method

No.	Date	Time	Place	Sampling	Amount	Analysis	TBS-H
0	06.10.2021	11:44:00	Barrel	Offline	500 ml	Phys. proerties	0.00
0	06.10.2021	11:45:00	Barrel	Offline	100 ml	Elemental+Phys.	0.00
1	22.10.2021	19:41:00	DV-T	Online	500 ml	Phys. proerties	391.95
1	22.10.2021	19:43:00	DV-T	Online	100 ml	Elemental+Phys.	392.00
2	09.11.2021	15:05:00	DV-T	Online	500 ml	Phys. proerties	427.40
2	09.11.2021	15:07:00	DV-T	Online	100 ml	Elemental+Phys.	427.39
3	20.11.2021	21:30:00	DV-T	Online	500 ml	Phys. proerties	270.42
3	20.11.2021	21:35:00	DV-T	Online	100 ml	Elemental+Phys.	270.47
4	01.12.2021	10:15:00	DV-T	Online	500 ml	Phys. proerties	252.75
4	01.12.2021	10:18:00	DV-T	Online	100 ml	Elemental+Phys.	252.72
5	10.12.2021	15:50:00	DV-T	Online	500 ml	Phys. proerties	221.58
5	10.12.2021	15:54:00	DV-T	Online	100 ml	Elemental+Phys.	221.60

NOTE: DV-T = Directional Valve after T port sample place; TBS-H = Time Between Sample is taken in hours (time is expressed individually for 100ml samples and 500ml samples, respectfully).

6.2.3 AUTOMATIC PARTICLE COUNTER (APC) AND WATER SATURATION (WS) SENSOR

APC (ISO 4406 particle measurement) monitors 24h hydraulic fluid contamination during the experimental investigation. The particle counter used is HYDAC CS1220 (Figure 44). The instrument is mounted online with a recording rate every 10 sec. Monitoring is done 24h daily since the machine is working for three shifts. Moreover, measuring water saturation is done by AquaSensor HYDAC AS2000 (Figure 44). Temperature is used as a feature from both instruments and correlated with variables to detect potential effects between the variables. Although temperature strongly affects viscosity, performance and system response, due to its effect on hydraulic fluid, the fluid temperature measured never surpassed the temperature higher than 50°C. Even though the system works for 24h, however workload of the hydraulic system is maintained at around 25 bars (hydraulic system idle state). Therefore, the intensity did not increasingly affect the temperature rise in the system.

6.3 HYDRAULIC POWER DATA

6.3.1 FLOW AND PRESSURE MONITORING DATA

Flow and pressure monitoring data is done via MultiHandy 2045 HYDROTECHNIK (Figure 44). The device measures on-site real-time data at the recording rate of 50ms, 100ms and 1000ms. Namely, the data has limited records data about 65000 storage records. Hence, the data for 20 cycles, taking into account that it requires approximately 2 minutes to start performing a hydraulic cycle, usually takes around 40-50min to record 20 hydraulic cycles. Therefore, aside from recording 1000ms, to gain exact insight into system degradation, 50ms per 20 cycles is used for diagnostic purposes for storing records of two memory channels, pressure and flow, respectfully.

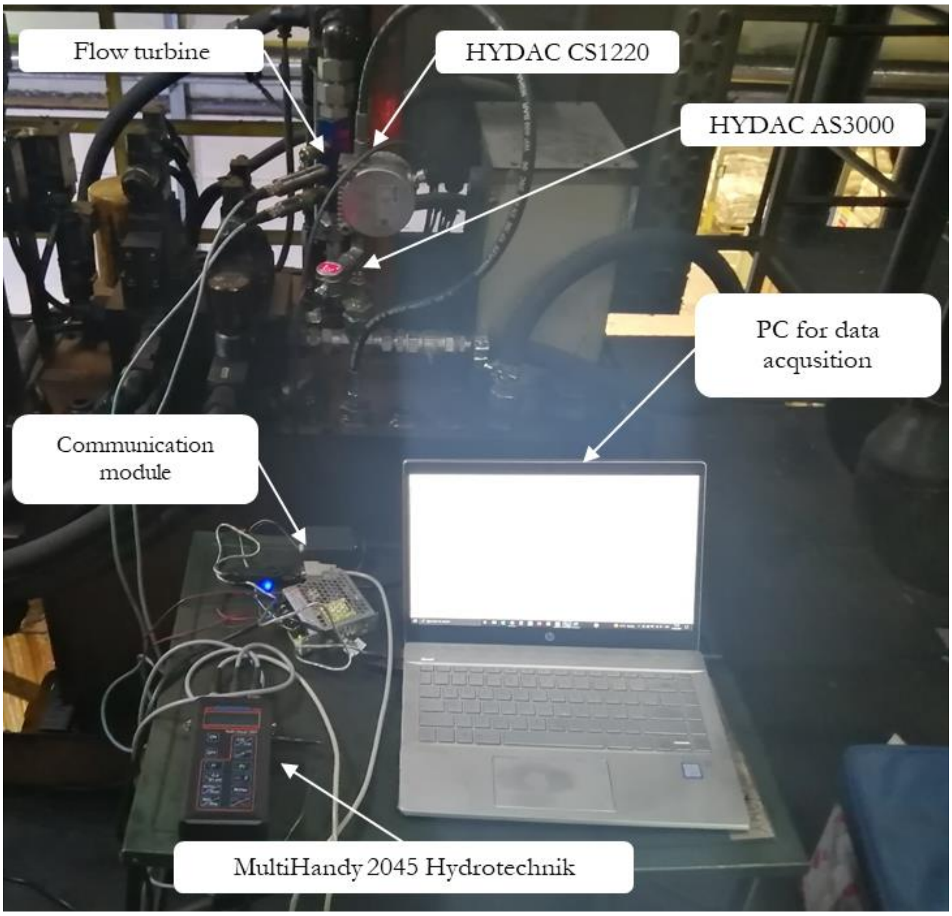


Figure 44. Experimental installation of mixers' hydraulic control system

Setting the experiment monitoring interval, the author first performed 1000ms monitoring to understand the intensity of production batches, deviations, potential stoppages, disturbances, preventive activities, etc. Although 1000ms does not provide valid information for diagnostic purposes by evaluating pressure and flow anomalies, they can be a good source of information regarding hydraulic system failures or stoppages. For instance, a pressure drop to 0 can be observed at the 3900-sec mark. Moreover, around the 4500sec mark, slight disturbances also happened, caused by deviations in directional valve response due to electronic issues. Monitoring flow and pressure are performed via MultiHandy 2045, and HydroCom software (Figure 45) is used for data acquisition. Monitoring flow and pressure for establishing hydraulic power variables are performed at a 50ms data acquisition frequency.

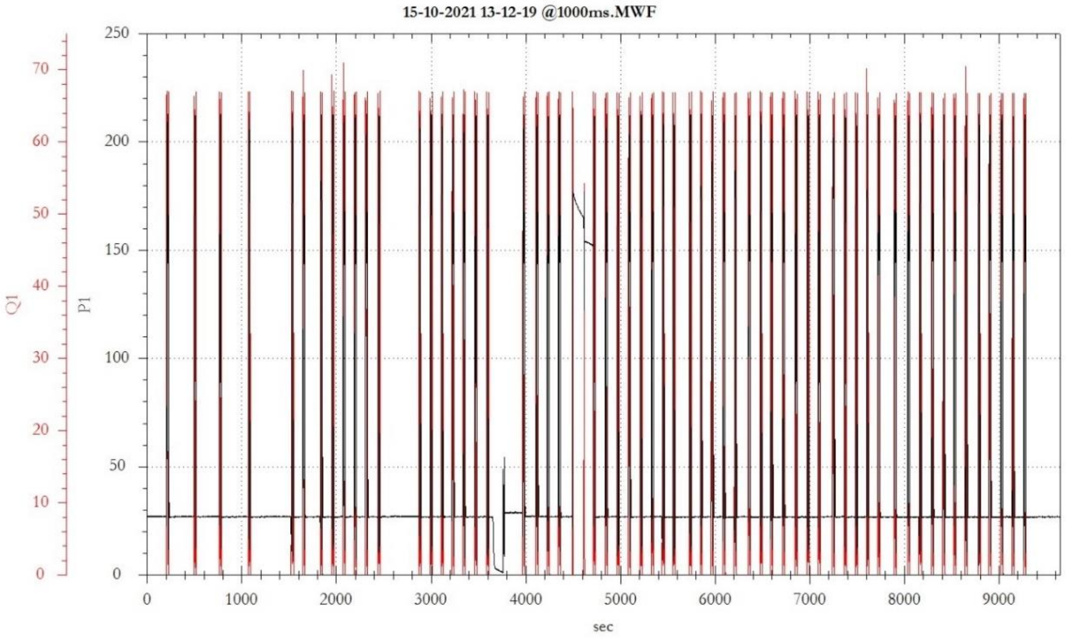


Figure 45. Records of pressure and flow via Multihandy2045 via HydroCom

An example of a stored record of a specific hydraulic cycle at 50ms is depicted in Figure 46.

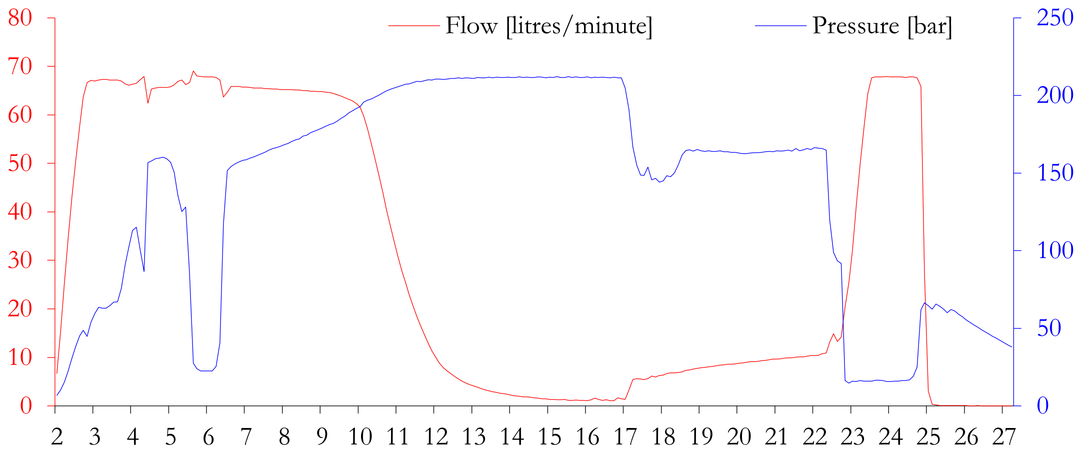


Figure 46. Single signal flow (y_1-axis) and pressure (y_2-axis) at 50ms record rate

Given the acquired information about a hydraulic system work (Figure 43) and its functional dynamics, the observed graph (Figure 46) can determine anomalies.

6.3.2 Actuators' response data – saddle opening and closing

The importance of utilising actuator response is to measure the dynamic response of power transfer. Since the model considers functional-productiveness, where the concept includes adding the productivity as a dimension of functionality, measurement of working cycles (time for each cycle) is vital. At the same time, monitoring actuators' response time (Figure 47) is used for setting labels in learning classification.

Figure 47. Saddle operation activation for 20 cycles

Since the regulation of the movement is controlled by directional valves, which are like pumps and other contaminant-sensitive components prone to degradation, it will also be used to determine whether there is an influence between their response and contamination. Besides, the idle position between unloading the rubber mass and closing the saddle is also used to penalise or confirm whether the system is in operating condition.

6.3.3 SCADA System data acquisition

The data processing machine's SCADA system synthesises and filters data important for the experimental study. Such data includes the date and time of every cycle; cycles performed for each batch; mass weight for specific batch production, cycles performed/planned; time for performing the cycle; temperature value inside the mixer; batt pressure/position; energy consumption; binary value for chamber filling [open, closed], and binary value for saddle [open, closed]. All of these values are filtered and sorted for data modelling.

Table 24. Example of SCADA information obtained for specific batch cycle

t [s]	Temp. [°C]	Bat_pos [%]	B_Pres [%]	Step	EC [kWh]	Saddle	Cham.
1	73.73	0.00	1.02	1.00	0.00	0	0
2	73.45	0.00	0.90	1.00	0.01	0	0
			...				
150	107.18	100.00	77.97	9.00	16.11	1.00	0
151	106.55	100.00	77.63	9.00	16.12	0.00	0

Even though SCADA provides value for opening and closing in seconds, a stopwatch is used to determine the exact rotation speed of the rack and pinion cylinder, i.e., opening and closing of the saddle. Additionally, recordings of mass weight load on the saddle and cycle time are used to determine whether there is an influence, i.e., correlation with the movement of the actuators or their response time.

It is also of interest to use evidence of performed cycle time of individual batches and hydraulic cycles (Figure 48) to see whether there is a correlation between the two since it affects the intensity of cycles performed due to stoppages outside of the hydraulic control system, thus potentially affecting temperature rise-drop. Moreover, it is also of interest to use hydraulic cycle times since a saddle, which is under the effect of a sensor that detects fully open and closed position, i.e. triggering directional valve control, was not working, indicating stoppage of a system.

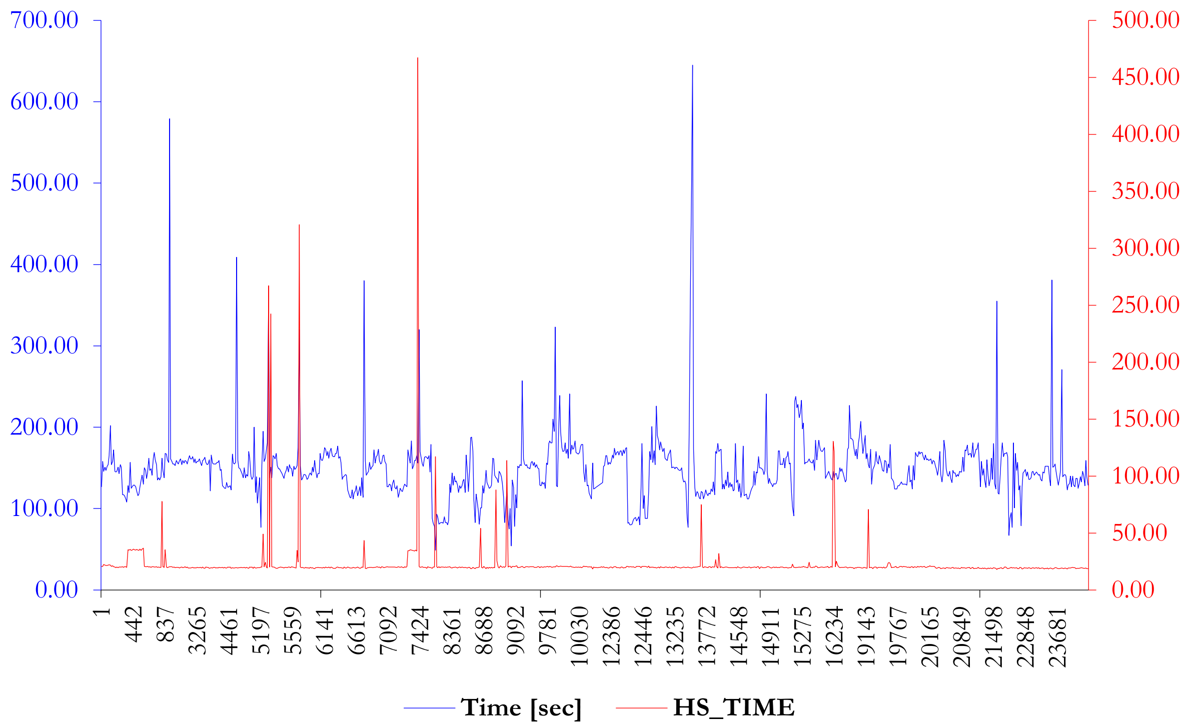


Figure 48. Time for performing cycle (y_1-axis) and hydraulic cycle time (y_2-axis)

7 EXPERIMENTAL RESULTS AND DISCUSSION

7.1 LABORATORY EXPERIMENTAL (OFFLINE) RESULTS

7.1.1 LABORATORY ANALYSIS OF HYDRAULIC FLUID PROPERTIES

Numerous physio-chemical analysis important for making conclusions on the state of the hydraulic system is available, although viscosity, density, water content, TAN, flame point, and flow point are amongst the most important one for making appropriate conclusions. Amongst all variables, the author used the measurements of Viscosity (at 40°C and 100°C), viscosity index, flame point, flow point, total acid number (TAN), density (g/cm^3) and water content (ppm) as the most important indicators. The samples are taken to two laboratories for a single-blind study to ensure the analysis's validity and transparency. The results are shown in detail in Appendix 2 and Figure 49.

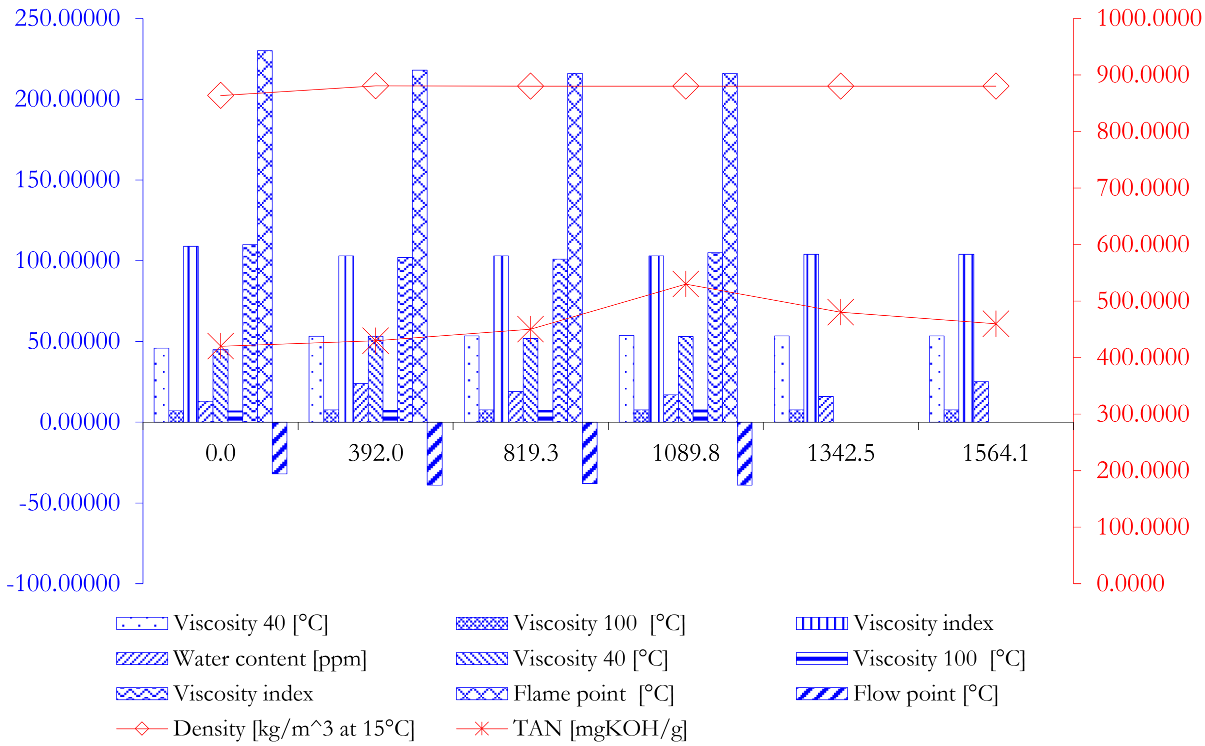


Figure 49. Fluid data analysis properties

The rubber mixing manufacturing process includes harsh environments due to the high temperature of the mixing machine, dust and moisture due to the watering process for cooling the rubber mixer process mass, i.e., the chamber. The maintenance department conducted maintenance activities such as filter replacement, oil refilling, and sensors replacement during the experiment. After these maintenance activities, it has been noticed that there is a sudden drop in particle contamination and slight "refreshment" (drop) in viscosity and density. After the second oil sample was taken (820h), the viscosity (40°C) results showed a slight decrease in the oil sample taken from one lab (500ml sample) while in the other lab showed a slight increase (100ml sample). Other properties like water saturation decreased and maintained somewhat in the stable range; however, almost all other properties started to increase in the second to last and last sample. Anomaly is that 500ml samples after the first sampling period show decrease in physical properties, while samples from 100ml show an increase in values after the first sample. So the question stands open, whether or not the sampling amount affects the results obtained? Water content shows a slightly higher increase in the final sample taken at 1500h, as seen in the increase of wear metal particles discussed in the following.

7.1.2 Elemental analysis of hydraulic fluid contaminants

The elemental composition of wear debris in hydraulic systems usually includes elemental analysis of iron (Fe), aluminium (Al), silver (Ag), copper (Cu), lead (Pb), molybdenum (Mo), chrome (Cr), Tin (Sn) and Nickel (Ni). The content of Fe is one of the most common wear metals found in fluid samples. The iron is associated with the wear of bearings, pumps, piston rods, pump housing, etc. Although exemplified in the analysis, low levels of Fe (warning 5-15 ppm) were not noticed until the last sample, which rose to the warning limit. It can be known that the comparison of ppm per 120litres of oil and 200litres after refilling shows an obvious increase in ppm since 80 litres of fluid have been added. Some have reported that sudden increases and decreases of Fe do not show an apparent problem and are usually denoted as an "anomaly of the pump" [125].

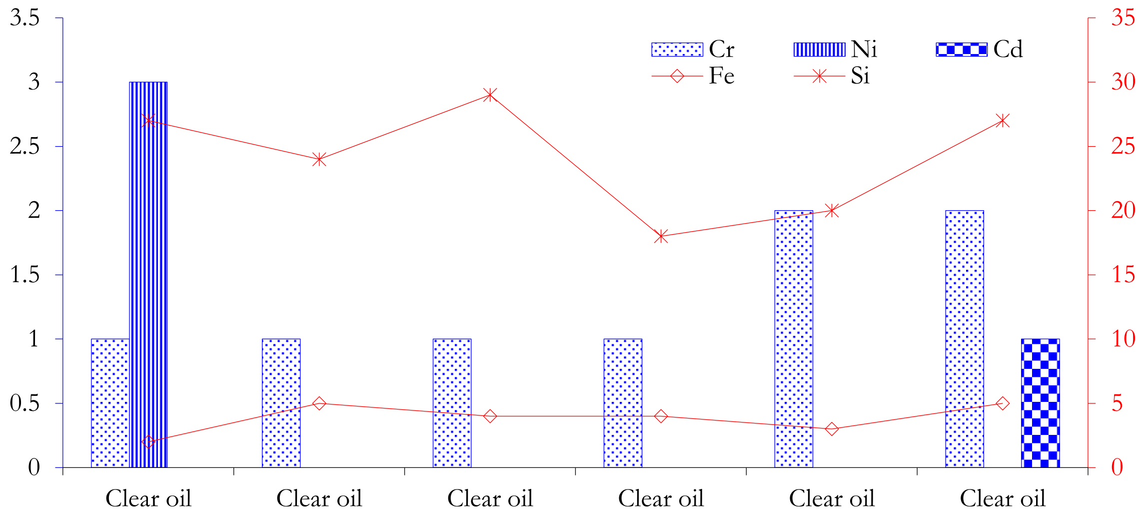


Figure 50. Elemental analysis of Cr, Ni, Cd (y_1-axis) and Fe, Si (y_2-axis) over time (x-axis)

Considering that no wear metals such as Ag, Al, Sn, and Mo were not detected in the oil sample will not be a point of further discussion. The point that Sn, Pb, and Mo increase are all associated with engine parts and coatings of compression rings can be excluded from the analysis. Interestingly, by comparing relative quantities of metals, the concentration of each wear metal varies significantly and can be in negative regression compared to each other. For instance, levels of Nickel, which usually range between 0-0.7 [125], here is up to 3 ppm at the start of the test, suggesting that at the very beginning, there may be the detection of wear since Ni is usually used as an alloy for surface coatings. Typical Ni-based coatings used on machine components play an important role in enhancing friction characteristics, i.e., increasing wear resistance or improving corrosion resistance [126]. In addition, Ni provides a hard, corrosion-resistance surface to resist wear and harsh working conditions.

Moreover, as an element with high hardness, nickel is also an excellent abrasion resistance alloy and is used as weldments applied over steel surfaces to protect the component from abrasive wear and is usually used in pump elements [126]. If Ni results from wear, specifically abrasive-induced wear (bearings and gears), if correlation remains proportional to levels of Fe or other metals like Cr, Ti, Mo, or V; it can suggest that these metals are alloyed; however, if the other wear metals increase disproportionally, it suggests coated steel parts [127]. Ni can be associated with coatings like chromium of elements such as valve stem packings (valves), bearings, gears, and shafts [128]. Hence, it also suggests that Ni is used for plating and as an alloying element in different oil-wetted hydraulic components and cast iron and stainless steels that usually contain a significant amount of Ni [129]. There are also reports supporting such behaviour from the analysis, where Ni starts to deplete, where only trace amounts of Ni in oil suspension can be recorded beyond the 150h mark [125]. Marlowe [130] reports that within the first and second hydraulic fluid sample, Ni had 1.0 ppm and 0 ppm, respectively, while in the filter sample, 2.0 ppm Ni was detected.

Evidence implies that wear metal concentrations tend to come close to some equilibrium in the system. Although some reports suggest that degradation can be associated with pump wear, further non-destructive reports do not provide evidence. It may conclude that the maintenance activities (adding oil) and replacing the filter drastically influence the oil characteristics showing that wear of the pump may have occurred; however, it may appear latent just by looking at the oil analysis results. In addition, it is extremely important to emphasise that using WDXRF for wear elemental analysis is questionable due to their LLD (lower limit detection) sensitivity in detecting particles lower than ten ppm.

7.2 STATISTICAL HYPOTHESIS TESTING OF ACQUIRED DATA

7.2.1 INVESTIGATING THE ASSUMPTION FOR CORRELATION HYPOTHESES TEST

In order to test the $\mathbf{H_3}$ hypothesis, the first supporting premise hypothesis ($\mathbf{h^{31}_0}$) tests the effect of the relationship between APC readings (ISO 4406) and hydraulic power delivery from the pump to actuators. Since *Pearson's r* coefficient highlights the strength of the linear relationship between the variables, it is important to investigate the basic assumptions. The basic assumptions consider (1) level of measurement; (2) related pairs; (3) absence of outliers; (4) linearity. The first assumption considers that variables are continuous, which is respected only for the HyPower variable; however, it is not for the particle counter level of ISO code since it is an ordinal scale variable. The "related pairs" consider that each measurement has a corresponding other, i.e., pair of values. The absence of outliers refers to not having outliers in either variable. An outlier can skew the variable data, pulling the best fit line formed too far from each other. Outlier testing is done with *Grubb's* outlier testing (Table 25).

Table 25. Grubb's test for outliers

Variable	*n*	mean	st. dev	min	max	G	*p-value*
APC 4	980	20.871	0.563	18	22	5.1	0.000
APC 6	980	20.552	0.666	17	21	5.33	0.000
APC 14	980	16.920	0.593	15	19	3.51	0.393
HyPower	980	0.0357	0.036	0.0033	0.0054	0.0586	0.000

The linearity implies that a straight line is formed between the tested pairs, i.e., a scatterplot shows the linear distribution of x and y values. Implicitly, the assumptions above state that both variables should be normally distributed (Table 26) and linearity and homoscedasticity (equal distribution of residuals around the regression line). Hence, since the data shows the presence of outliers, the same data will be removed and tested; in other instances, non-parametric *Spearman's* ϱ is chosen instead since it does not carry any assumption about the data distribution.

Table 26. Anderson-Darling normality test

Variable	*n*	mean	st. dev	min	max	AD	*p-value*
APC 4	980	20.813	0.609	18	22	127.32	0.005
APC 6	980	20.480	0.744	17	21	122.87	0.005
APC 14	980	16.913	0.628	15	19	109.67	0.005
HyPower	980	0.036	0.036	0.005	0.052	32.06	0.005

Because only the APC14 value does not break the assumption that there are no outliers (Table 25), all values are not to be considered normally distributed (Table 26) according to tested values of the *Anderson-Darling hypothesis test*, the non-parametric *Spearman test* is used. In such a case, since an extreme amount of data is processed and analyzed, normalization will be necessary for later analytical models (data reduction, feature selection, and classification).

The basic assumption is that contamination affects internal leakage due to pump wear and, presumably, loss of hydraulic power. Although the information regarding contamination level value (Appendix 3) does not provide the exact value of particles but rather a rough approximation given by the ISO Code, data is tested through cycles monitored and hydraulic power loss. One would expect that values do not change with statistically significant difference over time; however, data obtained from roughly 24 000 cycles (online monitoring 980 cycles), i.e., 1608 machine working hours, show the presence of correlation (Table 27) with statistically significant effect ($p < 0.01$).

7.2.2 TESTING THE RELATIONSHIP BETWEEN CONTAMINATION AND HYDRAULIC POWER

Namely, *Spearman's ϱ* coefficient shows a negative tendency (ϱ=-0.189; $p < 0.05$) between particle contamination (APC4) and hydraulic power delivery, i.e., the higher the contamination, the less hydraulic power is delivered to the system. Also, particle contamination of APC6 shows a negative correlation (ϱ=-0.230; $p < 0.05$) with hydraulic power delivered to the system. This is, presumably, a low effect of a correlation. However, APC14 does not show (ϱ=0.046; $p = 0.172$) the presence of the effect within the two. The rest of the data show a reasonably high correlation between the change in physical fluid properties, especially between density-viscosity (ϱ=0.81; $p < 0.05$), while also the change in density rise, as a consequence of contamination, shows a moderate negative correlation with power delivery to the system (ϱ=-0.52; $p < 0.05$). Therefore, there is insufficient evidence to reject the null concerning APC particle counts measurements.

The ISO class code cannot fully describe the exact correlation with other factors because the ISO code does not fluctuate enough to show the correlation effect between the ISO code and hydraulic power. Firstly, during the monitoring of the experiment, it has been noticed that particles do not change significantly (between ISO 15-17), thus not creating enough effect between the two. Secondly, the fluctuation of APC4 and APC6 readings from ISO 16 code to ISO 22 code has been noticed, questioning the influence of such small particles (air and water droplets). It also poses the question of filterability and the beta ratio of the filter since there have been two instances of the effect caused by maintenance activities – filter replacement and refilling the fluid in the system. Thirdly, the pressure filter in the main pressure circuit is β_{10} creates bias, meaning it stops particles ≥10 microns. Thus, suggesting the less variability of APC14 particles within the system. Finally, an APC is set not immediately after the pump but downstream of the system, thus influencing the effect of correlation with particle rise and hydraulic power delivery after the pump.

Table 27. Correlation matrix – APC readings and hydraulic power per cycle

	HS (t)	HS_iddle	kg/n	APC 4	APC 6	APC 14	Dens	VISC40	HyPower	VI
HS_idle	-0.08									
[kg]/n	-0.13	0.28								
APC 4	-0.09	0.01	-0.11							
APC 6	-0.21	0.05	-0.03	0.72						
APC 14	-0.09	0.17	0.06	0.44	0.58					
Density	-0.21	-0.31	-0.22	0.24	0.29	-0.13				
VISC40	-0.22	-0.37	-0.23	0.24	0.25	-0.15	0.81			
HyPower	0.26	0.20	0.11	-0.19	-0.23	0.01	-0.52	-0.61		
VISC-INDX	-0.02	-0.13	0.16	-0.27	-0.31	-0.05	-0.35	-0.13	0.41	
VISC100	-0.10	-0.34	-0.26	0.30	0.26	-0.13	0.63	0.90	-0.47	-0.12

The ISO Code 6 depicts that particles ≥6 μm show potential wear intensity happening in the system, thus increasing the density measured in this example. Although the particles show a low tendency (negative correlation) on hydraulic power delivery, it is also the subject of debate about the effect of particle wear contaminants and particle contaminants like water and non-wear-metal particles like *Si*.

7.2.3 RELATIONSHIP BETWEEN FLUID PROPERTIES CHANGES AND HYDRAULIC POWER

It is shown that hydraulic power is under negative correlation with density (ϱ = -0.276; $p < 0.01$), leading to the conclusion that there could exist an indirect relationship proven by density change over time, however, filterability of particles causes bias in estimating the root cause of wear through elemental analysis. An anomaly in the relationship between Ni and Zn could indicate wear. Namely, after the first sampling period, there is a slight decrease in Zn and an increase in Ni, which could be a potential argument for wear. Fe and hydraulic power have a small linear relationship (ϱ = -0.235; $p < 0.01$), which could indicate potential material loss and internal leakage.

Table 28. Correlation matrix – the relationship between LCM and hydraulic power

	HyPower	Density	VISC40	VISC100	Water [ppm]	Zn [ppm]	Ni	Fe	Cr
Density	-0.517								
VISC40	-0.614	0.805							
VISC100	-0.466	0.634	0.903						
Water	-0.068	-0.249	-0.462	-0.485					
Zn	0.437	-0.751	-0.855	-0.807	0.674				
Ni	0.437	-0.751	-0.855	-0.807	0.674	1			
Fe	-0.437	0.751	0.855	0.807	-0.674	-1	-1		
Cr	0.193	-0.225	-0.06	-0.129	-0.701	-0.269	-0.269	0.269	
Si	0.05	-0.068	-0.304	-0.499	0.03	-0.03	-0.03	0.03	0.52

However, the author argues that such causality analysis needs further investigation to support such claims, and from such a small sample, exact results could not be taken as a final statement since it only reflects a tendency towards logical presupposition.

The underlying reason is that contamination in this case, i.e., wear elements, does not directly show the relationship of influence between contamination and loss of power; in fact, the relationship is shown through overtime loss of power through the wear of a pump. It is also under scientific debate the sensitivity of WDXRF spectrometry since elemental analysis readings below 10ppm are questionable with this instrument.

For gaining more insight into the behaviour of LCM data, a correlation heatmap with hierarchical clustering is depicted in Figure 51. It can be seen which parts of the elemental analysis and LCM physio-chemical data form clusters, i.e., correlate between each other and with other hydraulic system indicators, especially considering the HyPower variable, suggesting low r values with LCM data.

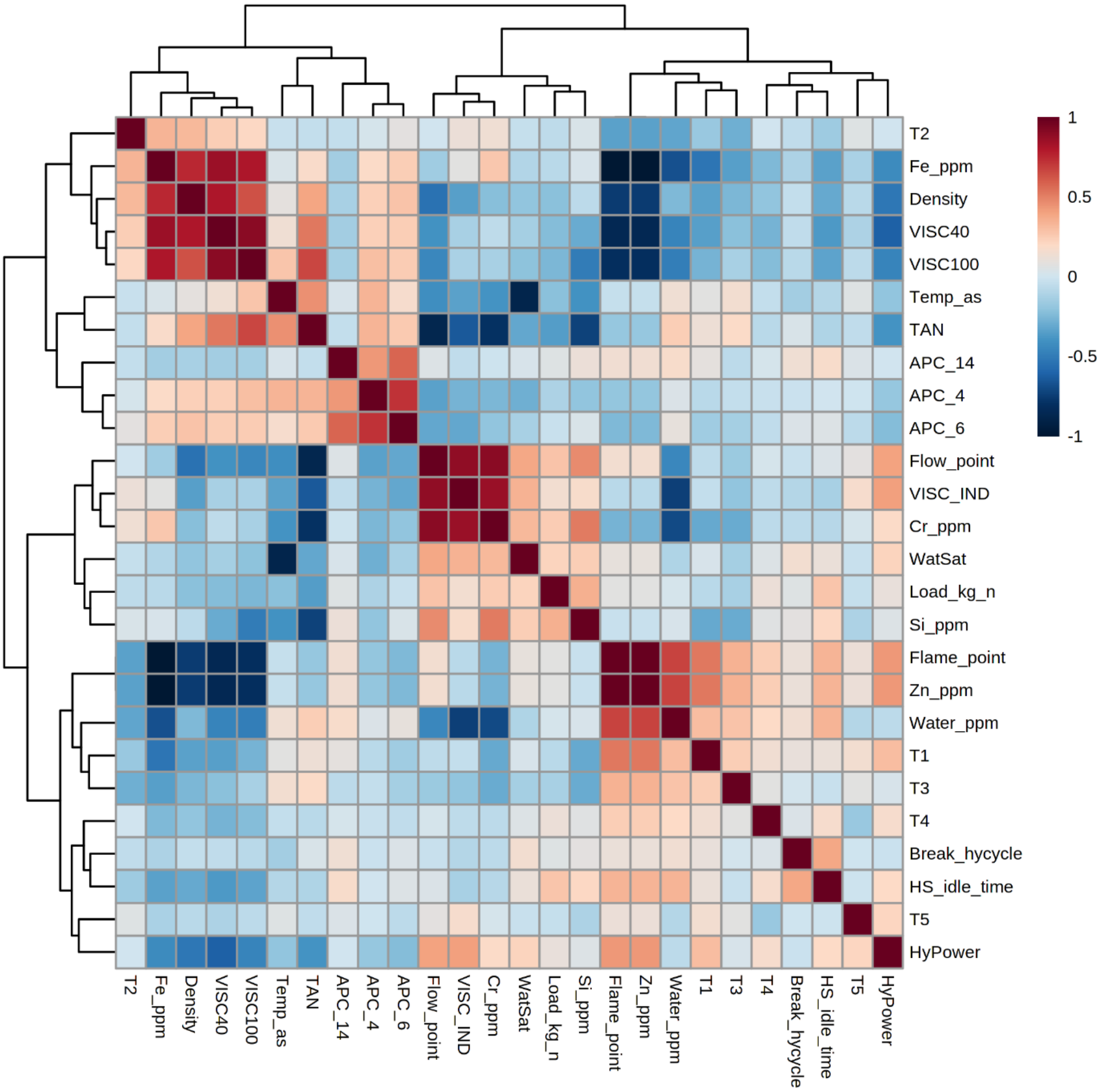


Figure 51. Correlation matrix heatmap with hierarchical clustering

7.2.4 Graphical interpretation and filtering of hydraulic power readings

As observed by the previous correlation analysis, results show poor intra- and inter-correlation presence of LCM data and HyPower. The difference between the two is that intra-relationship of LCM results shows effects of particle contamination increasing fluid density – suggesting wear and leakage of the pump and consequently reduction in hydraulic power delivery to the actuators.

Following such instance, and thus, monitoring power transfer through the system, one can detect power loss (degradation) and use this data for diagnostic and prognostic purposes. Figure 52 shows that a system response and power transfer degradation can be observed. From such a standpoint, and following the main premise that energy can be used for condition monitoring, the same will be used for ML hypothesis testing.

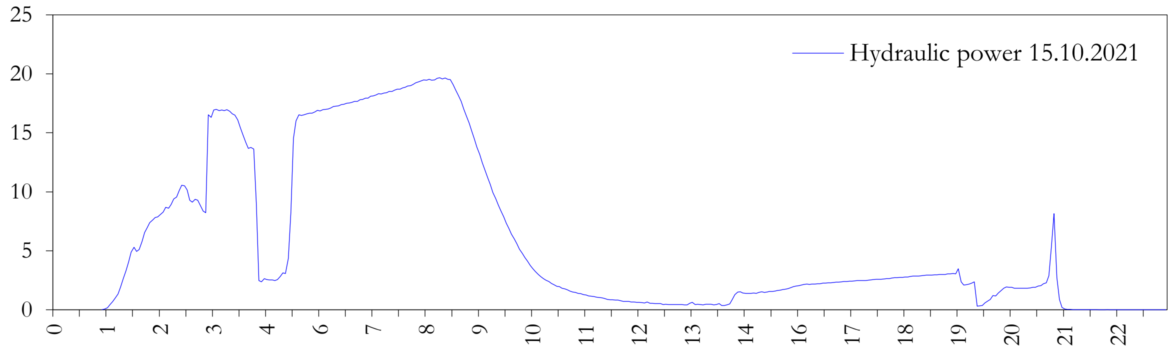


Figure 52. Hydraulic power readings (y-axis) per cycle (x-axis) stabilisation

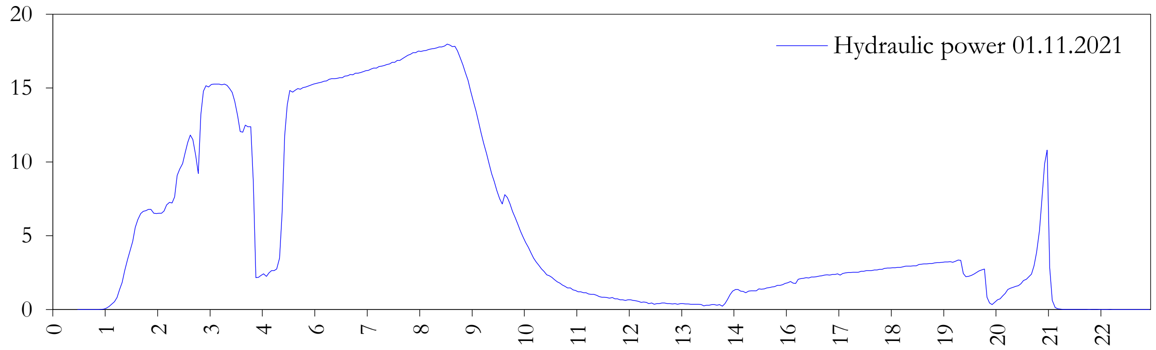


Figure 53. Hydraulic power readings (y-axis) per cycle (x-axis) stabilisation

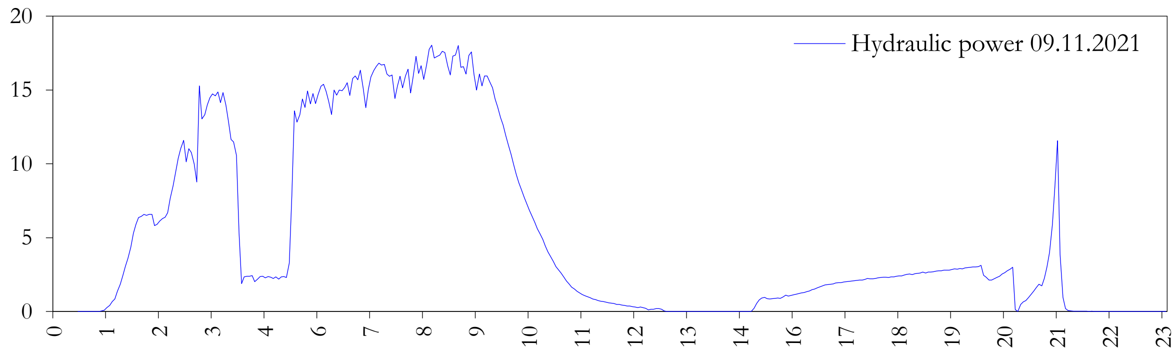


Figure 54. Hydraulic power readings (y-axis) per cycle (x-axis) anomaly

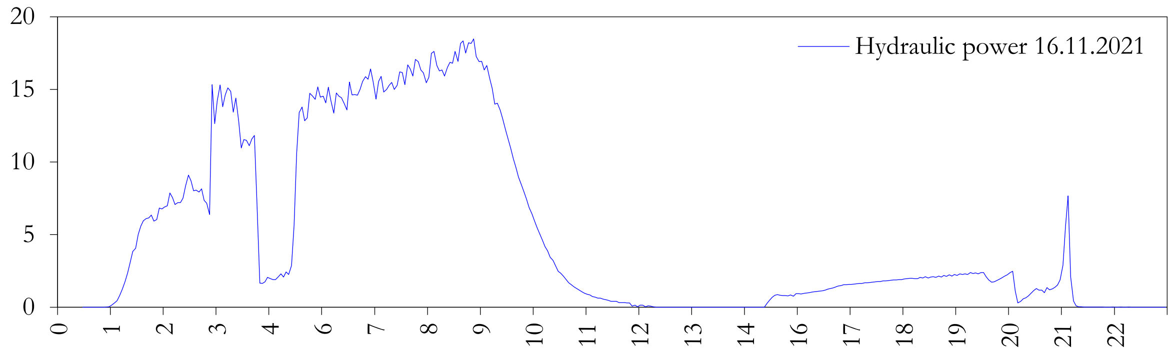


Figure 55. Hydraulic power readings (y-axis) per cycle (x-axis) end cycle anomaly

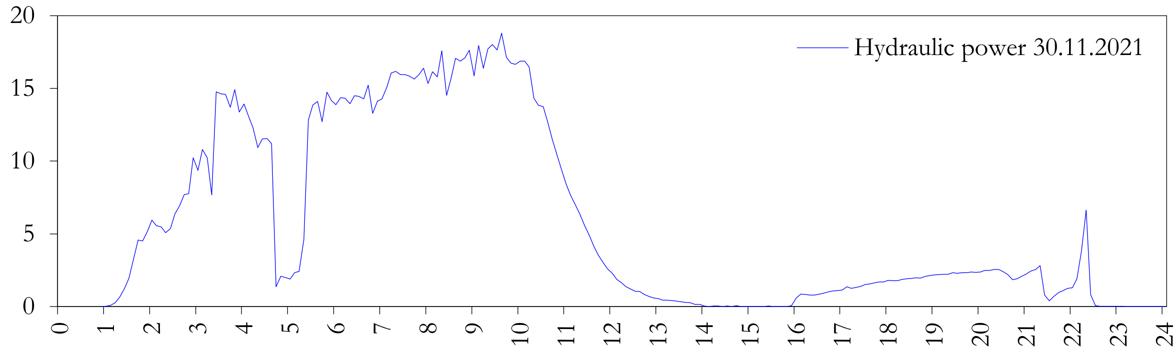


Figure 56. Hydraulic power readings (y-axis) per cycle (x-axis) deviation and time anomaly

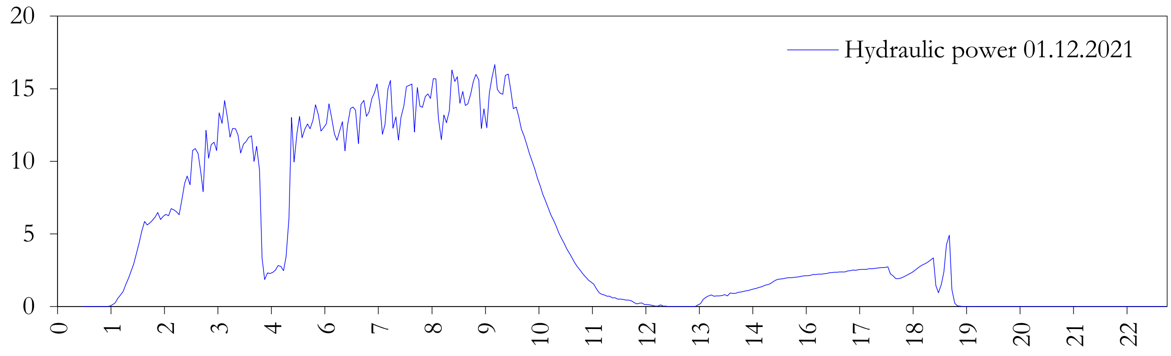


Figure 57. Hydraulic power readings (y-axis) per cycle (x-axis) deviation and time anomaly

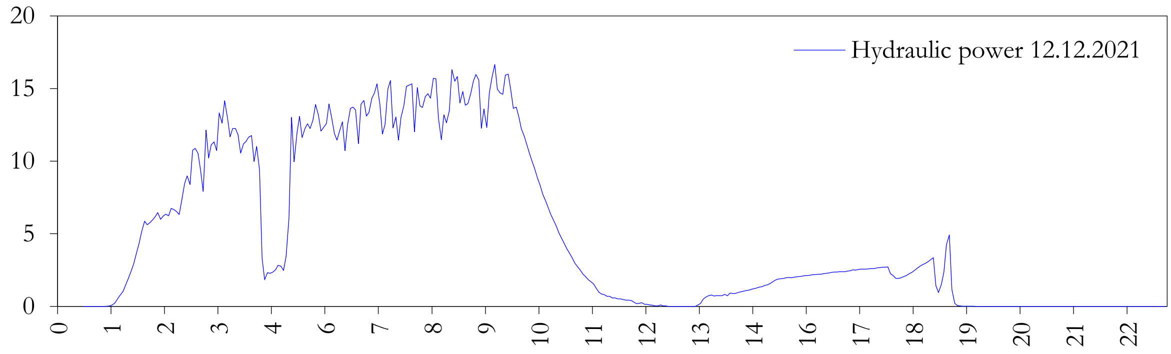


Figure 58. Hydraulic power readings (y-axis) per cycle (x-axis) deviation and time anomaly

Moreover, deviation of power signal can show different variations in system response and functionality of a system. For instance, observing the *x* and *y-axis* within a specific bin (sequence of signal, e.g. 1 sec) shows deviation in time (x-axis) and power (y-axis), hence, showing deviation in both axes in terms of functionality (power) and productivity (time). Therefore, monitoring both time and power suggests deviation in component response and power reduction (e.g., wear, leakage) of a specific component. This way, different noise in the signal is depicted in Figure 59.

It can be observed that, although with some amount of uncertainty and natural frequency of system behaviour, certain system states can be noticed, which are later labelled for machine learning testing. From a specific signal monitored $n = 20$ cycles, it is observed several deviations, such as delay in valve activation signal, closing saddle time (due to sensor reaction time), stoppage (saddle sensor off), early start of the cycle (valve activation), and finally normal operation of a system. As such, the proposed labelled sequences of cycles are labelled as "None" (normal operation) and "Quasi-fault" (faulty operation).

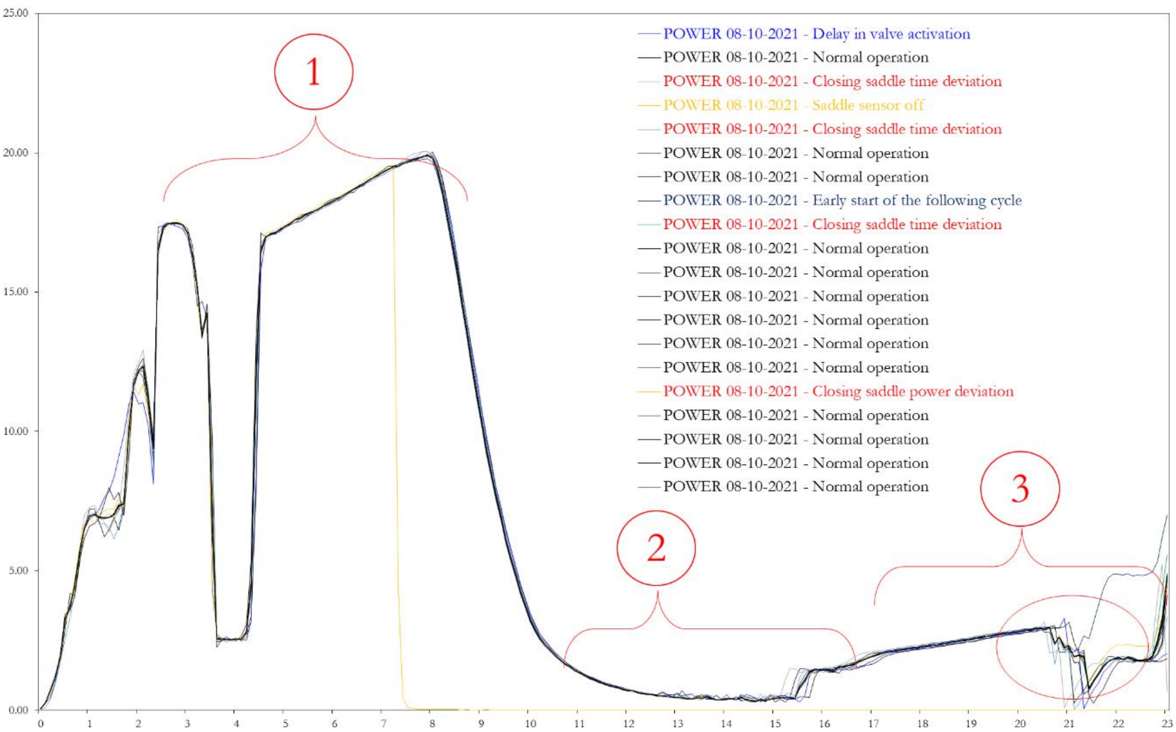


Figure 59. Deviation in response and hydraulic power measured (y-axis) in time (x-axis)

Data separation is done for the part of the hydraulic power signal, which was derived from the flow and pressure monitoring procedure and data extraction. The signal is then split into three main sequences: (1) opening saddle (OS) position – consists of opening saddle on the rubber mixing machine that is performed with retraction of linear (safety) cylinders and rack and pinion cylinder rotation for dumping the rubber mass; (2) idle saddle (IS) position – set for the explicit time by eliciting position sensor that is set automatically before returning into initial position; (3) closing saddle (CS) position – activated by position sensor triggering directional vales and forcing rack and pinion to return into initial position before linear (safety) cylinders fully extent into its initial position.

Data separation and discretization are important to better insight into the system state and detect potential anomalies that can be used with Association Rules (AR) for unsupervised learning to detect exact fault-induced mechanisms and potential failure. This is usually done by different tools, of which the easiest one is to do a correlation with possible anomaly change simply. Consequently, the author aims in future to split binary classification labels into multiple classification problems for an unsupervised learning approach. Therefore, it will be beyond the scope of the thesis.

8 MACHINE LEARNING DATA PREPARATION

Considering that data acquisition of the experiment is done in the previous steps by extracting relevant information from the SCADA system, LCM (hydraulic fluid analysis) and hydraulic power (flow and pressure), the explanation is given in the previous chapters. However, although the machine learning data processing (Figure 60) includes the first step of raw data collection, this reader may be referred to some of the previous raw data acquisition steps and analysis. The collection of SCADA operational data (see 6.3.3) is important as controlled variables in terms of system behaviour, anomalies, influences and data (also experiment) replication.

The LCM online and offline monitoring data (see 6.2.1) is important since the author of the thesis is arguing the lack of quantitative estimation of data extracted from the system, either online or offline. For instance, it was unable to determine the potential wear of the pump or elements just based on WDXRF since the instrument has debatable results of measurements below 10 ppm. In addition, measurements of particle counts by APC also cause suspicions regarding the number of solid particles present in the fluid, such as internal (e.g., wear) or ingressed (e.g., dust) particles, since the APC also causes bias in measurements by mistaking particles with water and air bubbles present in the fluid. Both WDXRF and APC, alongside with aqua sensor (saturation), did not suggest an increase in water and particles due to wear in the system.

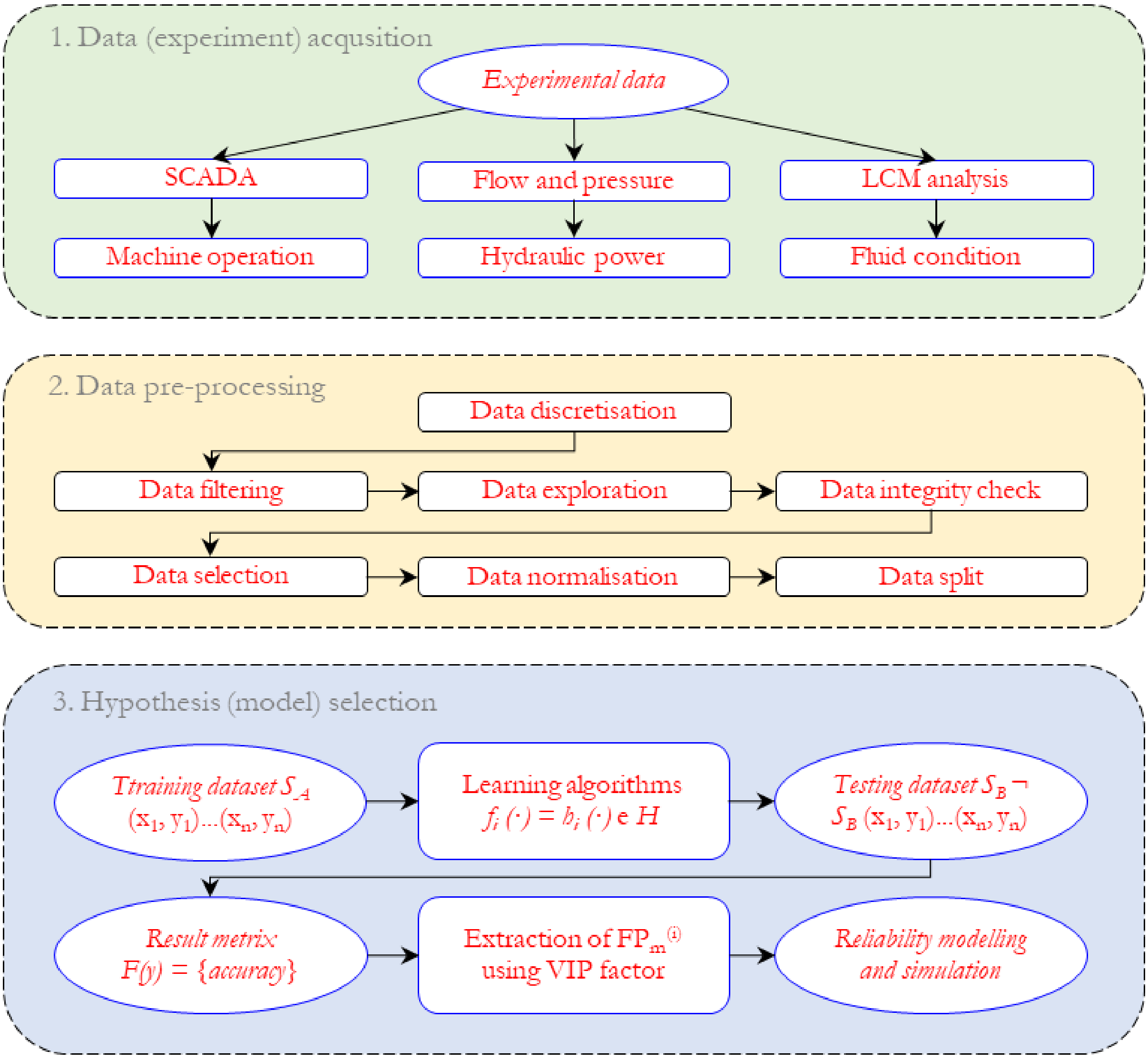


Figure 60. Flowchart of data processing and ML modelling

Initially, it was hard to establish the presence of contaminant-induced wear, and chemical degradation of oil since laboratory analysis (see 7.1) did not indicate the two possible outcomes. Therefore, by using flow and pressure, the inference is that the deviation in the signal can be used to estimate or detect potential anomalies since timely replacement of filters, oil refillings and oil replacement caused bias in determining the system health. Therefore, the author hypothesised that better estimation of the system health, in terms of operational stability, i.e., functional-productiveness, can be established by proposing markers estimated based on the hydraulic power delivery from the pump to the actuators, which are derived from pressure and flow monitoring. Therefore, the first step is to use *data discretisation* of the HyPower signal (see 7.2.4).

8.1 DATA (PRE)PROCESSING – DISCRETISATION AND FILTERING

Data discretization considers transforming a huge number of data (power signal reading) into smaller amounts for easier evaluation and management of data. In other words, it considers the transformation of continuous values into finite set values with minimum data loss, i.e., preserving the original values as much as possible. For the supervised learning approach, histograms are usually used to determine the frequency of continuous data by simply plots. This way, one can inspect the distribution of data, skewness, kurtosis, possible outliers, and other important factors. Since data of a specific signal consists of a specific set of time for performing a hydraulic cycle, the data is split into opening-, idle- and closing-saddle positions. All three possible states are then used to propose different significant and non-significant functional-productiveness markers based on the labelled states. The following formulas are used to establish markers for detecting signal anomalies:

Mean (**Average**) of *n* readings of a signal *N* for specific saddle position and specific cycle:

$$N\_MEAN\_XS = \frac{1}{n}\sum_{i=1}^{n} N_i \tag{8.1}$$

where *N* is amount is the HyPower data readings, *n* reading samples and abbreviation *XS* is saddle position, where *XS* will be abbreviated as *OS* = *opening saddle, IS* = *idle saddle*, *CS* = *closing saddle* position.

The standard deviation of *n* readings of a signal *N* for specific saddle position and specific cycle:

$$N\_StDev\_XS = \frac{\sqrt{(x_i - \bar{x})^2}}{n-1} \tag{8.2}$$

where $\bar{x}$ is the average value for a specific finite set of records for a given saddle position at a specific cycle.

Root mean square (**RMS**) of *n* readings of a signal *N* for specific saddle position and cycle:

$$N\_RMS\_XS = \sqrt{\frac{1}{n}\sum_i x_i^2} \tag{8.3}$$

First Quartile (**1Q**) of *n* readings of a signal *N* for a specific saddle position and the specific cycle is determined by ordering a dataset of *x* elements as $x_1, x_2 \dots x_n$ from lowest to largest, respectively. By interpolating data points from lowest to largest, we will find the ***%Q***th element if x_i is in the *i*/(*n*+1) quartile. Considering that quartile ranges are established as quartile per cent ranges are split as min, 25%, 50% and 75% and max, then denoting integer part of *a* by [*a*], then quartile function is:

$$N\_nQ\_XS = n(Q) = x_{(k)} + a\left(x_{(k+1)} - x_{(k)}\right) \tag{8.4}$$

where k = [Q(n+1)] and a = Q(n+1)-[Q(n+1)]. Therefore, finding 1st, 2nd, and 3rd quartile, i.e., 25%, 50% (Median), and 75% *n*th element we must find *n*(0.25), *n*(0.50) and *n*(0.75), respectively. The excel function „=QUARTILE.EXC()“ with *array* and *quartile* arguments provides an easy way to extract quartile values, where the values are extracted for all three quartile ranges, including the ***interquartile*** (**IQR**) range of data spread between 3rd and 1st quartile, and defined as:

$$N\_IQR\_XS = \mathrm{N\_3Q\_}XS - \mathrm{N\_1Q\_}XS\,. \tag{8.5}$$

In addition to quartile ranges and previous formulas, minimum and maximum values are also calculated via the excel function as a **minimum** („=MIN(*array*)“) and **maximum** („=MAX(*array*)“) values of given *n* records of a signal *N* at a specified cycle. Peak to peak interval value is also calculated by subtracting maximum from minimum values as:

$$N\_P\_P\_XS = |\mathrm{N\_MAX\_}XS - \mathrm{N\_MAX\_}XS|\,. \tag{8.6}$$

Skewness is calculated as:

$$N\_Skew\_XS = \tilde{\mu}_3 = \frac{\sum_i^n (x_i - \bar{x})^3}{(n-1)\cdot\sigma^3}\,. \tag{8.7}$$

where $\tilde{\mu}_3$ is skewness as a third standardised moment in statistics; x_i is the random ith value, $\bar{x}$ is the average calculated value for specific saddle position, *n* records and *N* signal readings. In addition, to the 3rd moment, the 4th centralised moment, i.e., Kurtosis, is also used and given as:

$$N\_Kurt\_XS = \tilde{\mu}_4 = \frac{\sqrt{n(n-1)}}{n-2}\frac{\sum_i^n (x_i - \bar{x})^3}{(n-1)\cdot\sigma^3}\,. \tag{8.8}$$

All calculated values are used for data exploration by calculating all of the markers for each saddle position „regime“.

8.2 Exploratory data analysis and filtering of the FP markers

8.2.1 Exploration of data – opening saddle position

Investigating the relationship between hydraulic power (-energy) for selecting machine learning variables in diagnosing the state is done by separating the signal into three main bins: (1) Opening the saddle (OS); (2) Idle saddle (IS); and (3) Closing Saddle (CS). These three conditions are used to formulate variables of statistical significance.

Conducting filtering on OS data for eliminating statistically non-significant values (p>0.05), the results show that variables of "T3", "T5", N_IQR_OS, and N_Skew_OS are eliminated. The heatmap results show that saddle actuator speed time (T3, T4, T5) does not show any correlation between the variables used for evaluating saddle degradation, in addition to T2 (which could be associated with proportional valve opening position), idle time of the hydraulic system and load at the cylinders' side (Figure 61).

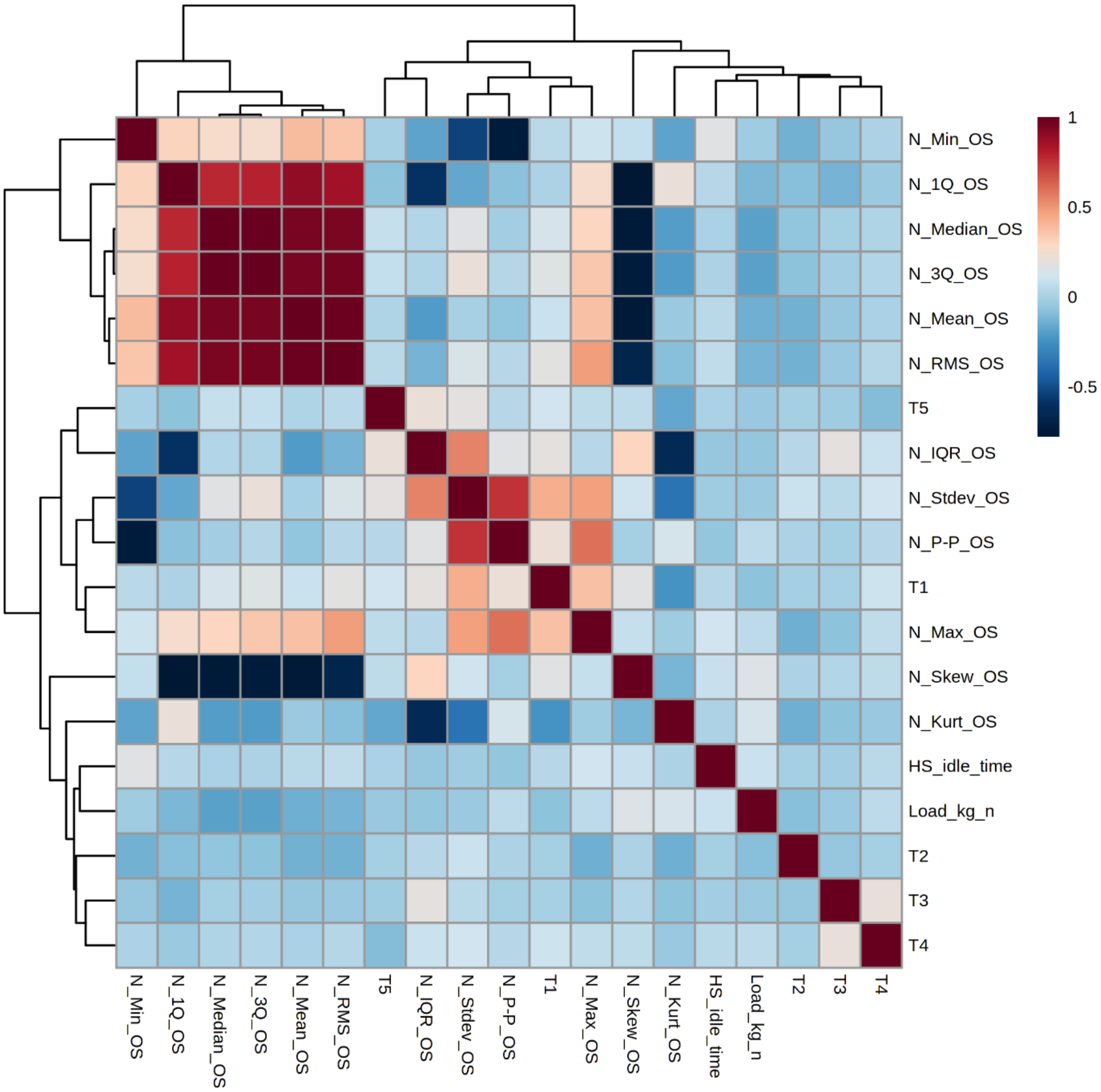


Figure 61. Correlation heatmap of variables included in the opening saddle position

In addition, to avoid multicollinearity of data, as it can be observed that mean and median values are highly correlated with each other and other variables, they need to be removed to obtain good machine learning prediction performance and reduce bias. After eliminating all of the non-statistically significant features, the results show that N_Max_OS (Figure 62); N_StDev_OS (Figure 63); T1 (Figure 64) and N_Median_OS (Figure 65) possess good classification properties.

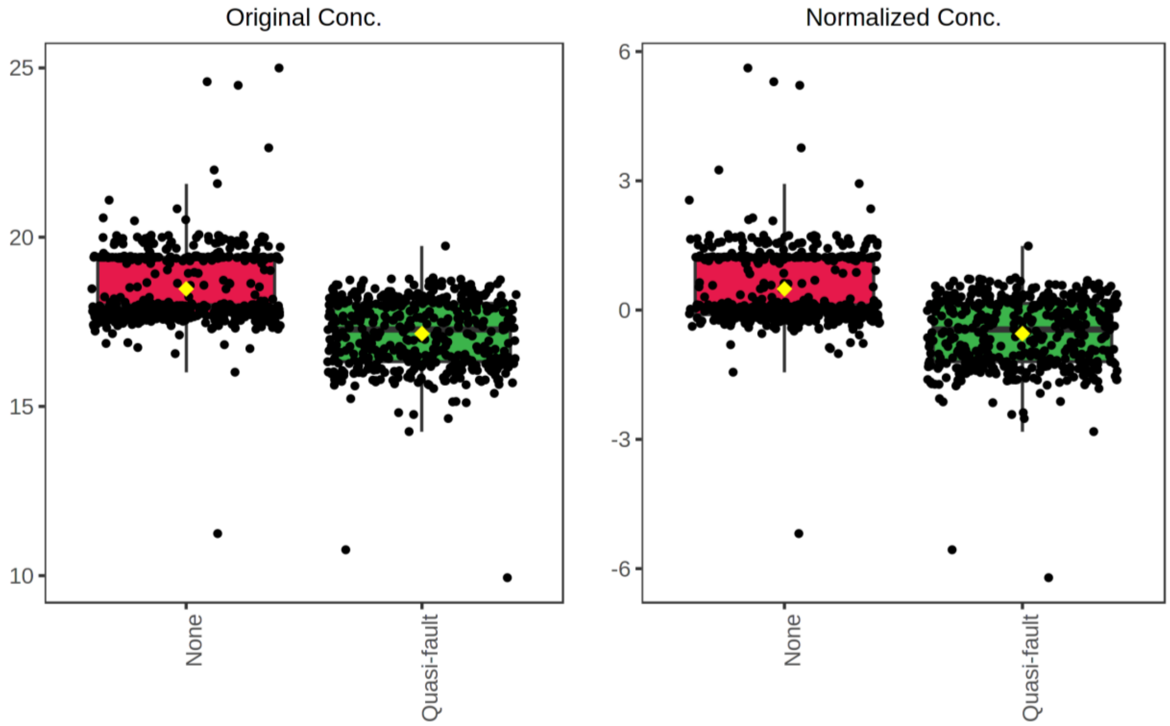


Figure 62. Box and whisker plot of N_Max_OS in opening saddle position signal

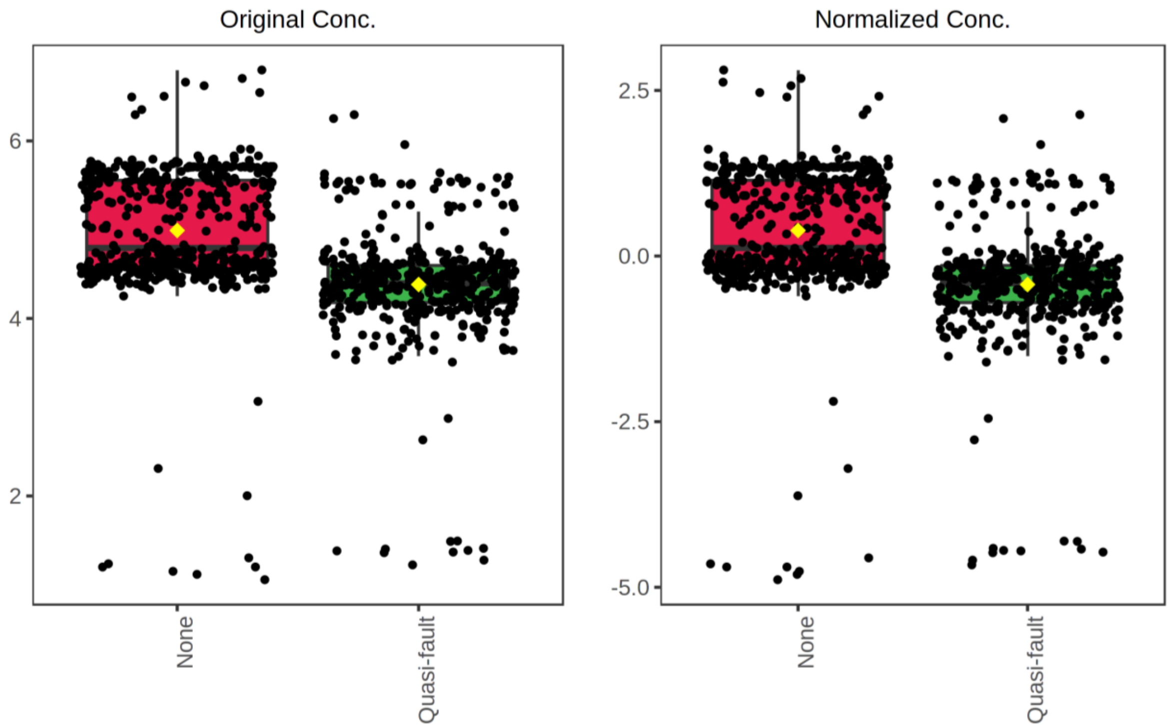


Figure 63. Box and whisker plot of N_StDev_OS in opening saddle position signal

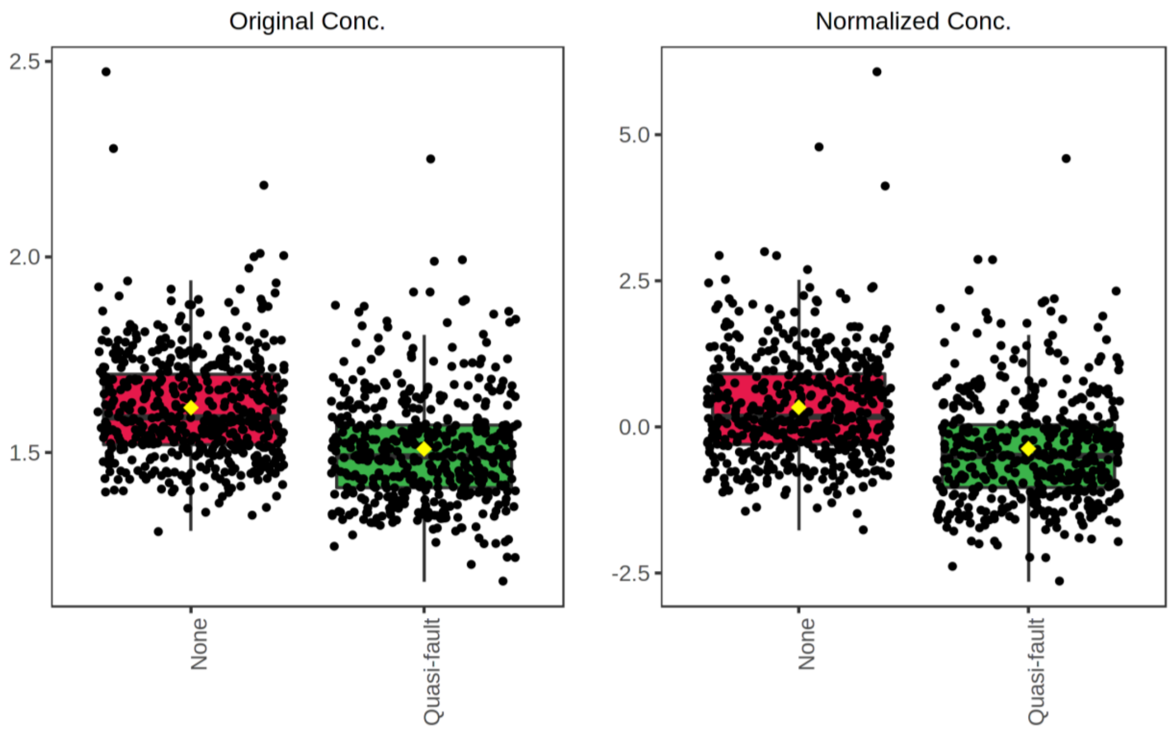


Figure 64. Box and whisker plot of T1 value in opening saddle position signal

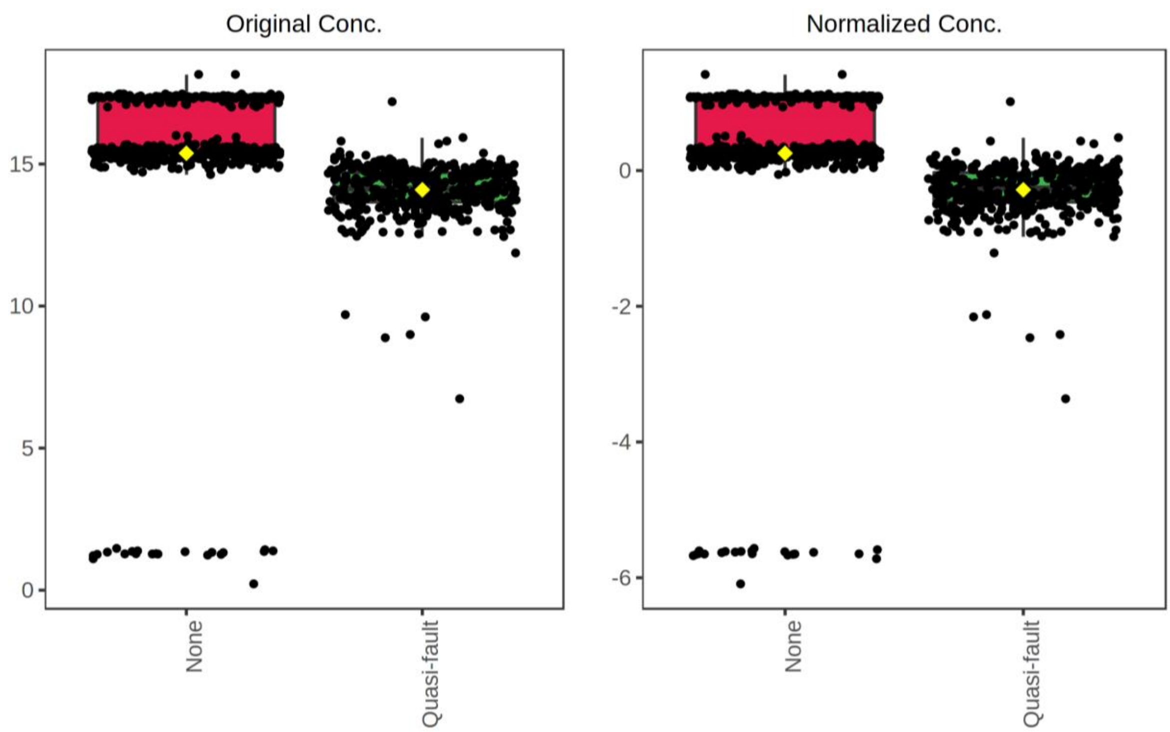


Figure 65. Box and whisker plot of N_Median_OS value in opening saddle position signal

Reviewing the obtained results of box and whisker plots, it can be seen that the N_StDev_OS (Figure 63), T1 value (Figure 64) and N_Median_OS (Figure 65) behave as features that have good mapping properties, i.e., variables that can be used for predicting labels, unlike N_Kurt_OS (Figure 66), N_Skew_OS (Figure 67), N_1Q_OS (Figure 68) and N_Kurt_OS (Figure 69). Since there may be inconsistency with data modelling, for the decision between mean and median, additional PCA for visualisation will be used to establish which variable has better prediction properties.

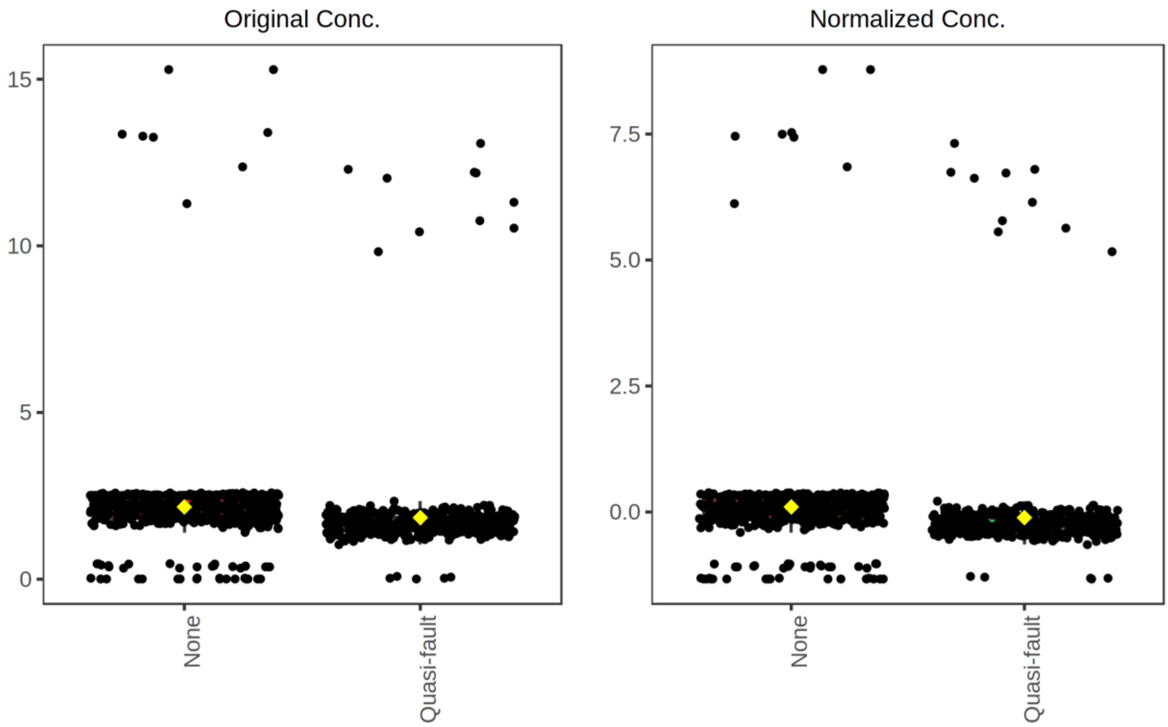


Figure 66. Box and whisker of N_Min_OS at opening saddle position signal

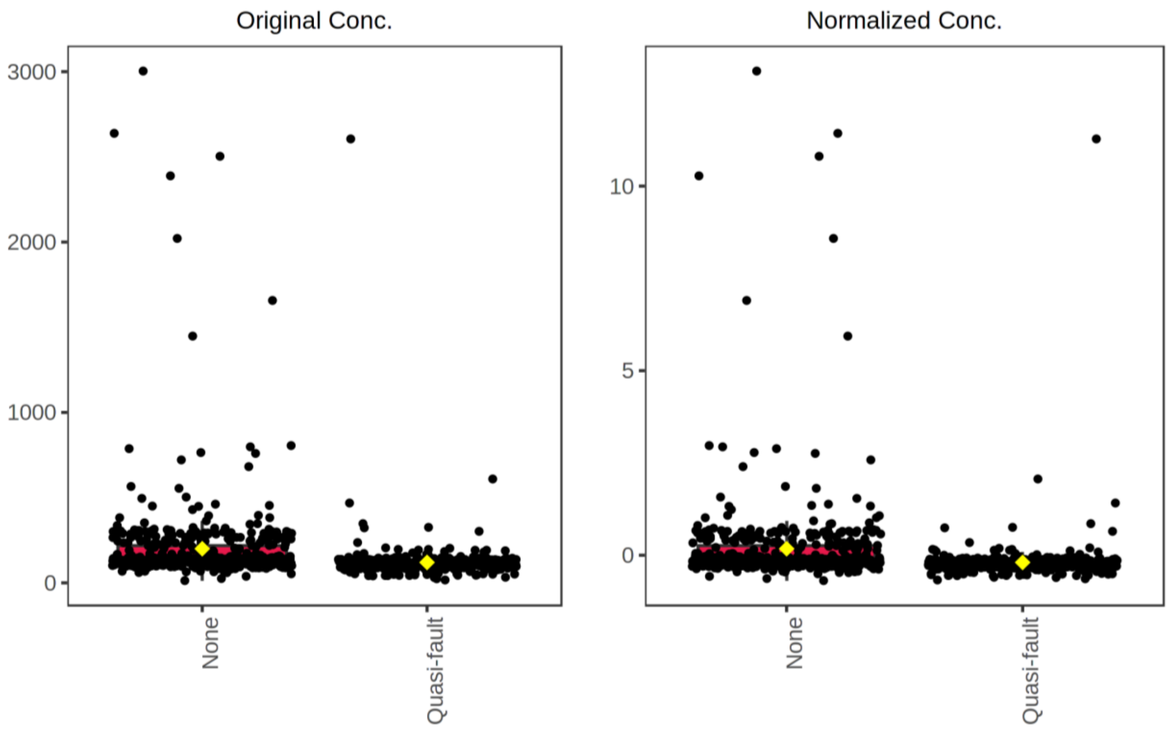


Figure 67. Box and whisker plot of N_HsIdleTime_OS at opening saddle position signal

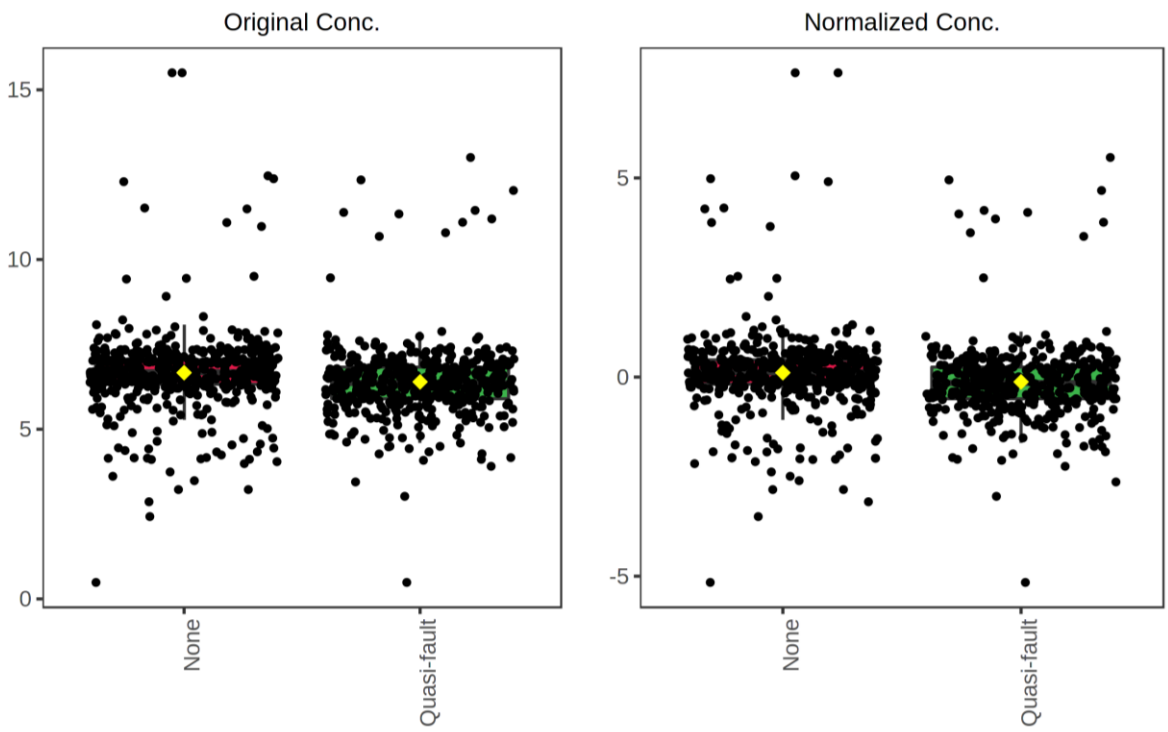


Figure 68. Box and whisker plot of N_1Q_OS at opening saddle position

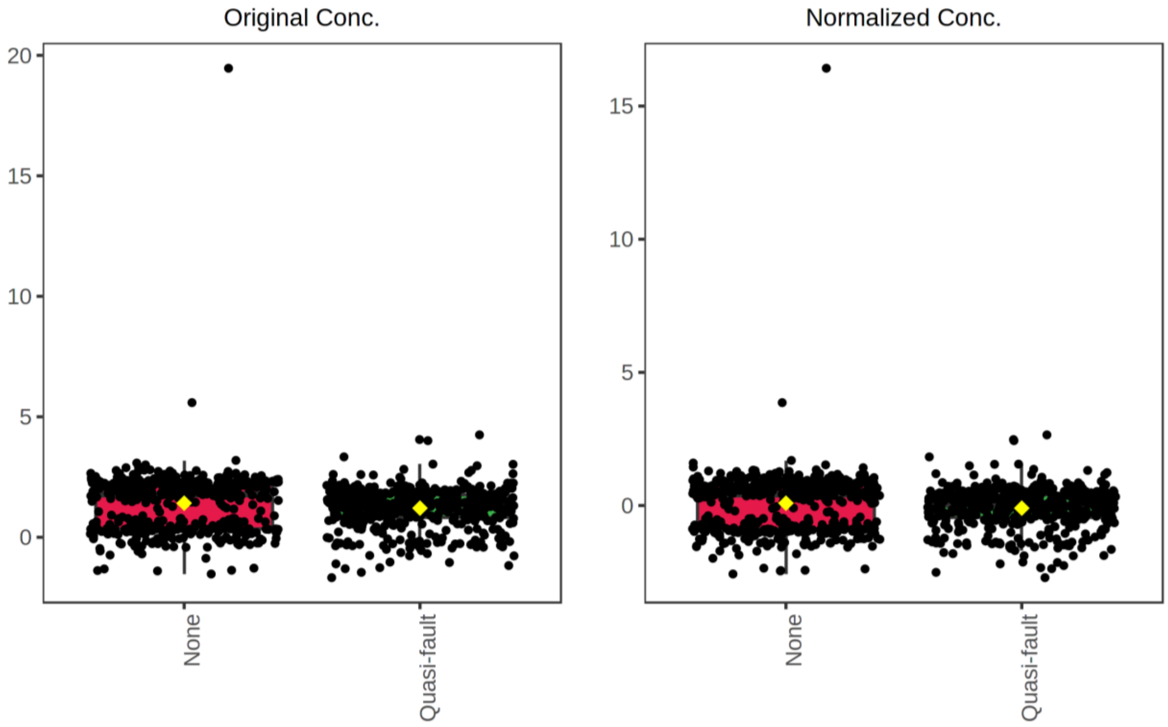


Figure 69. Box and whisker plot of N_Kurt_OS at opening saddle position

8.2.2 EXPLORATION OF DATA – IDLE SADDLE POSITION

Conducting exploration of IS data, the t-test showed that non-significant (p<0.05) variables are "Break_Hycycle", "T2", "T5", and N_Max_IS. Based on the rest of the variables obtained, the results show strong multicollinearity in the variables associated with the idle saddle position of the signal. In addition, since there are cases with the known prior condition of saddle improvement (new saddle sensor) and total failure due to saddle sensor detection failure, both sample datasets are removed as outliers. In addition, it can be seen on the correlation cluster heatmap (Figure 70) that the presence of multicollinearity must be eliminated from the variables N_3Q_IS, N_IQR, N_Mean_IS, N_StDev_IS, N_RMS_IS, and N_Kurt_IS with N_Skew_IS. Trial and error are used to estimate the best possible variables that explain most data variation in the samples/features.

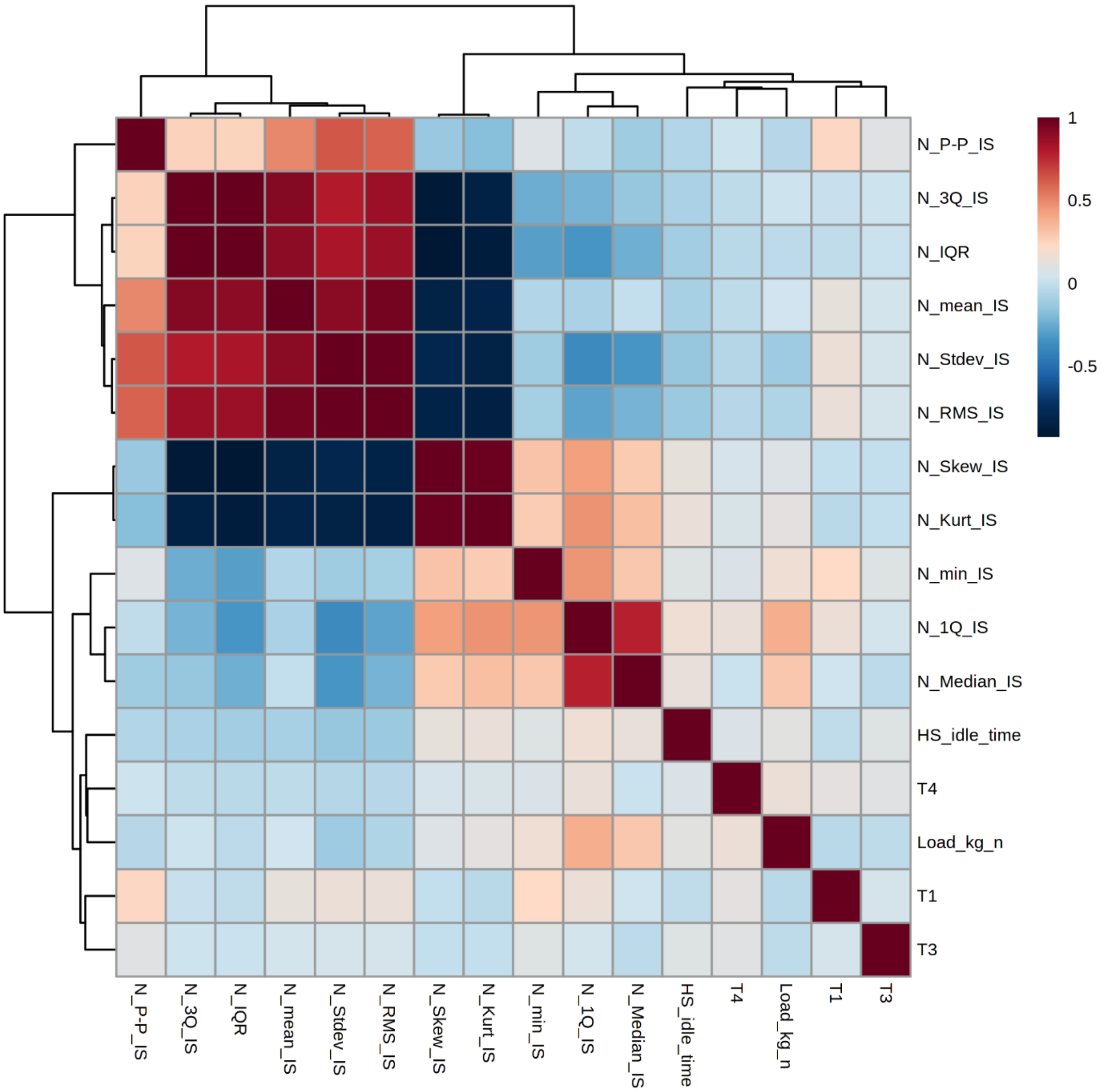


Figure 70. Correlation heatmap of idle saddle position signal variables

Finally, after eliminating all of the non-statistically significant features, the results show that 16 variables are statistically significant for the analysis. Namely, the most significant variable is shown to be N_1Q_IS (Figure 71), N_Kurt_IS (Figure 73), N_Median_IS (Figure 72), and N_StDev_IS (Figure 74), in addition to variables of min value, T1 and standard deviation of a signal at closing saddle position (assumption of multicollinearity).

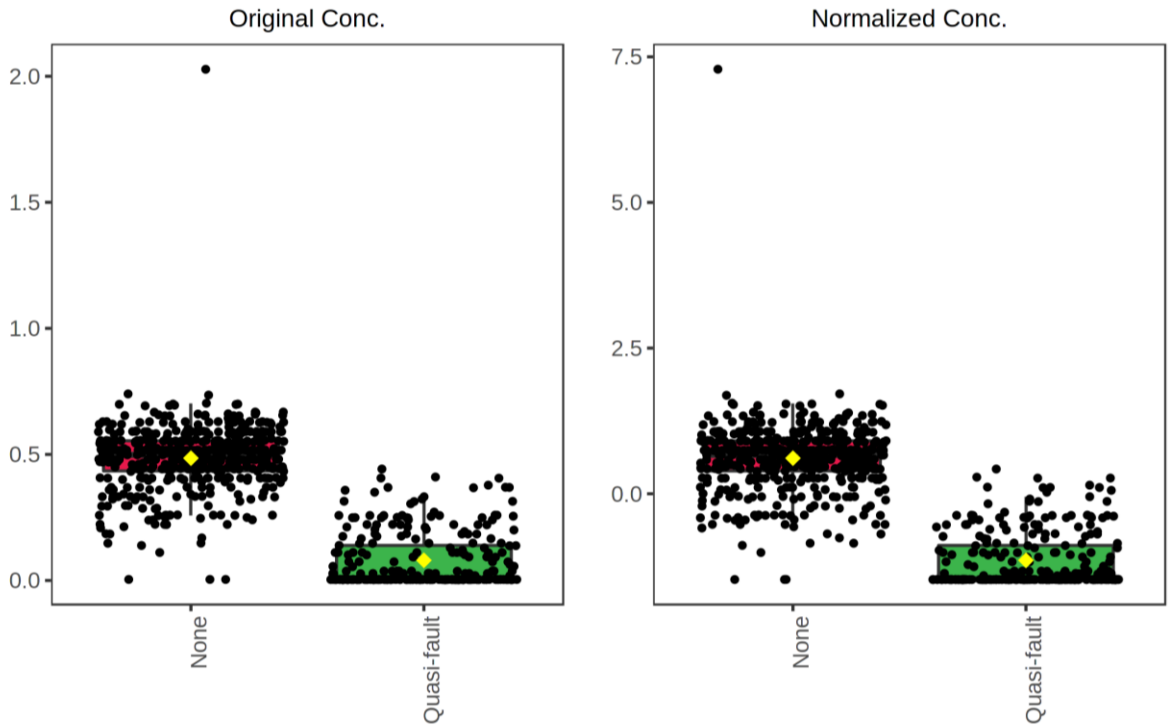


Figure 71. Box and whisker plot of N_1Q_IS value of idle saddle position signal

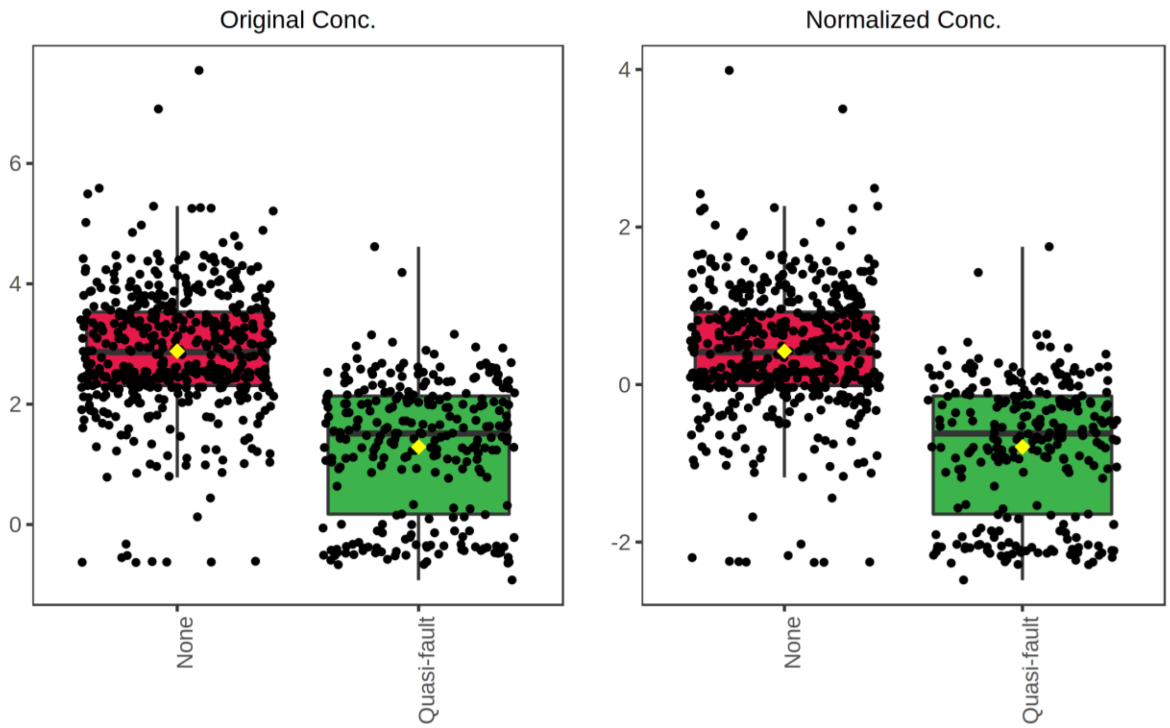


Figure 72. Box and whisker plot of N_Kurt_IS value of idle saddle position signal

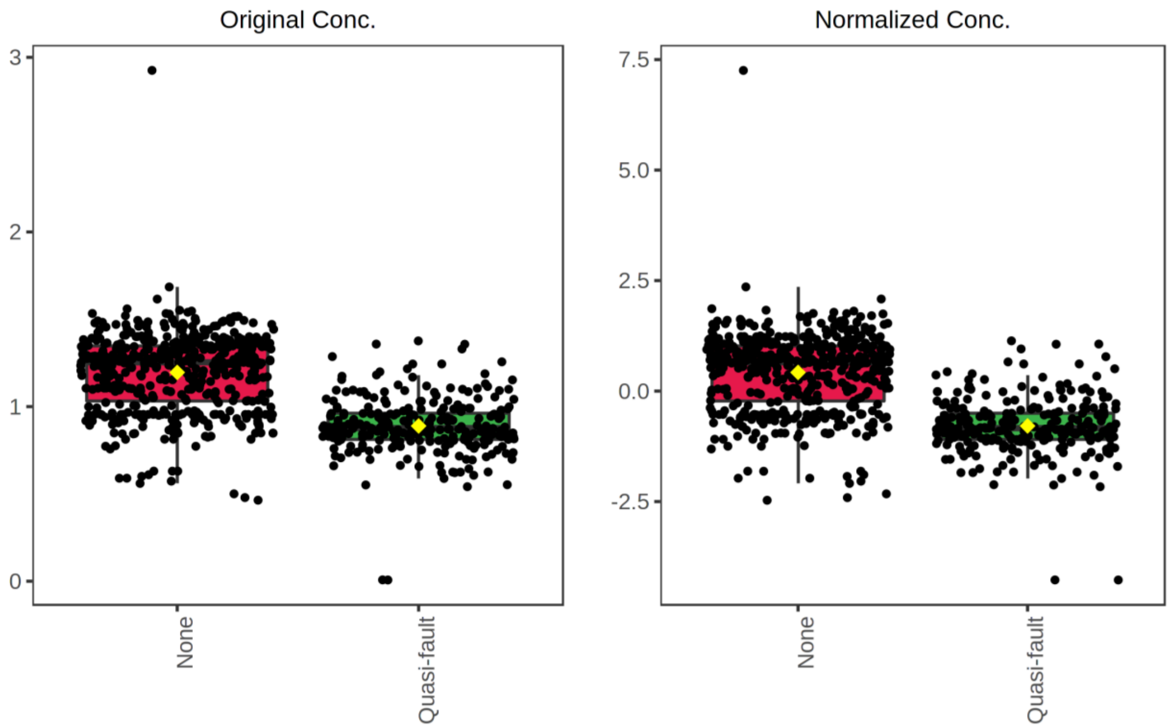


Figure 73. Box and whisker plot of N_Median_IS value of idle saddle position

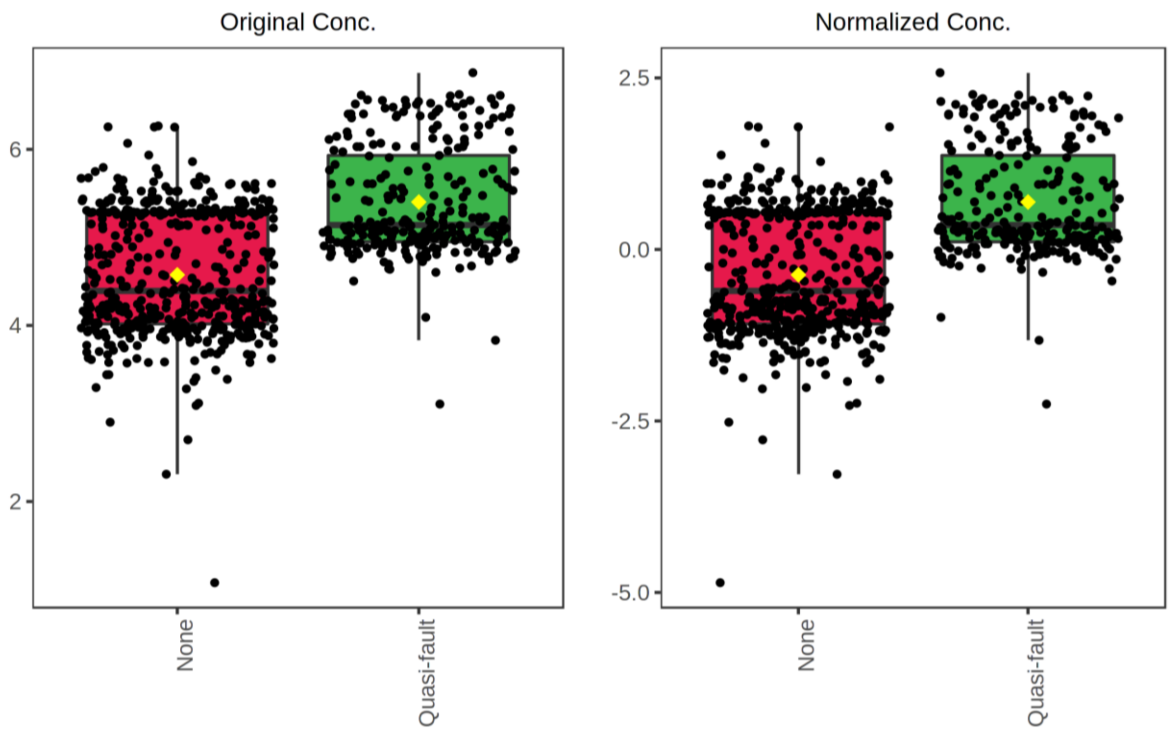


Figure 74. Box and whisker plot of N_StDev_IS value of idle saddle position

After reviewing the previous figures of statistically significant values, which can help improve prediction, i.e., classification results of normal and non-normal (quasi-failure) operating conditions, the classification will be done accordingly using the proposed FPMs.

8.2.3 Exploration of data – closing saddle position

The marker "Break_hycycle" in all three cases shows no relationship of a break between batch productions, i.e., turning on and off the hydraulic system and running again. However, it imposes the question of working temperature influence under the assumption of the negative effect temperature causes on hydraulic working fluid. However, although temperature causes a detrimental effect on hydraulic system performance (e.g., viscosity degradation), during the experimental investigation, the temperature did not cause any effect correlated with any of the physio-chemical parameters of the fluid. Therefore, breaks do not show a significant relationship here. As for the correlation, the *r* coefficient Figure 75 shows associated variables that cluster together, namely N_Max_CS and N_P-P_CS and N_Skew_CS and N_Kurt_CS (Note: Pearson*'s r* coefficient distance), suggesting multicollinearity between the variables. They are then excluded from the study using trial and error estimation and an additional PCA biplot.

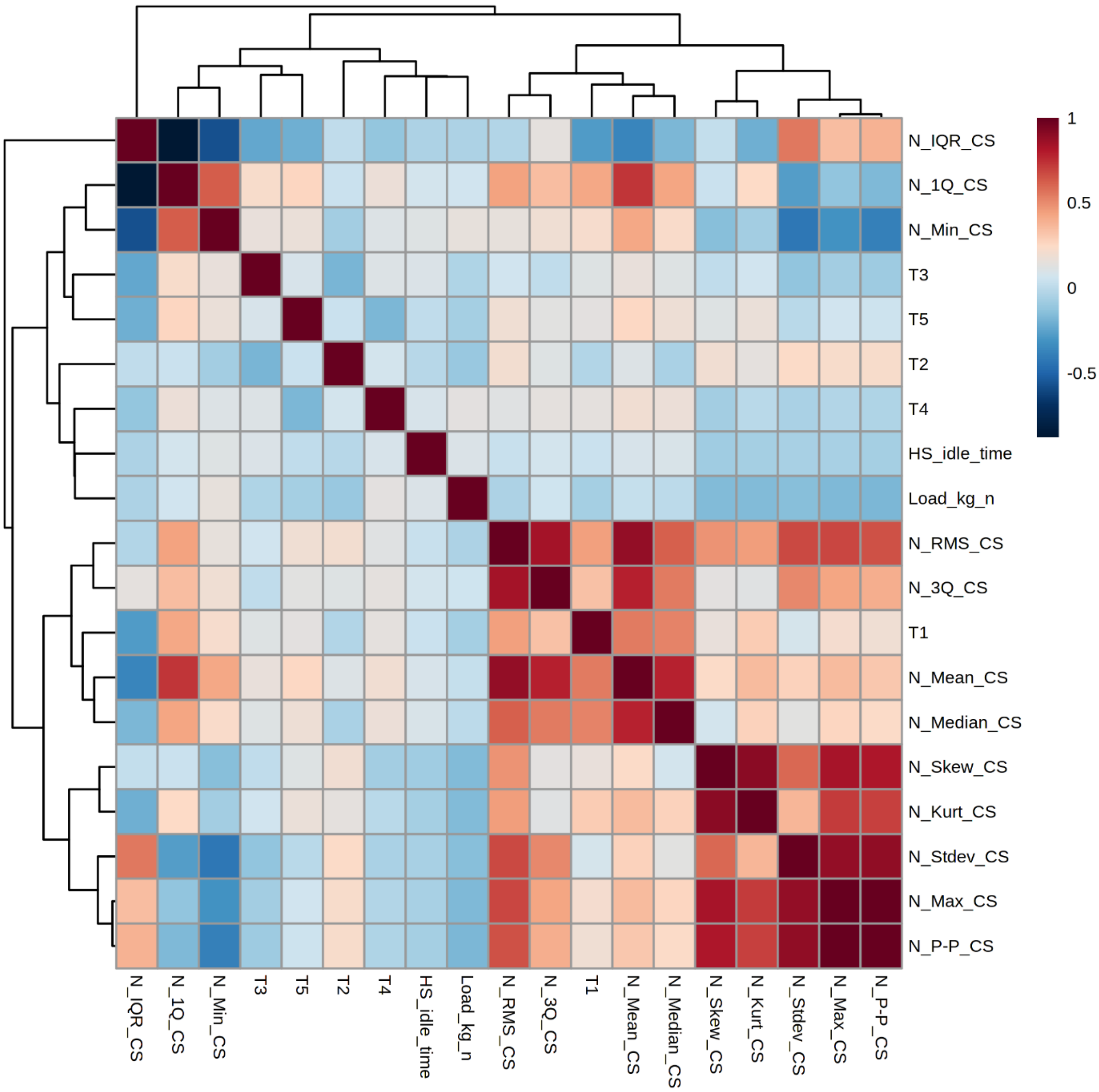


Figure 75. Correlation heatmap of the closing saddle position signal

Moreover, before visualising data plots using PCA for data visualisation and exploration. The box and whisker plot is used to evaluate separation effectiveness, i.e., mapping classifiers for discriminative purposes. The most significant variables show to be N_1Q_CS (Figure 76), N_Mean_CS (Figure 77), N_Min_CS (Figure 78), and N_IQR_CS (Figure 79).

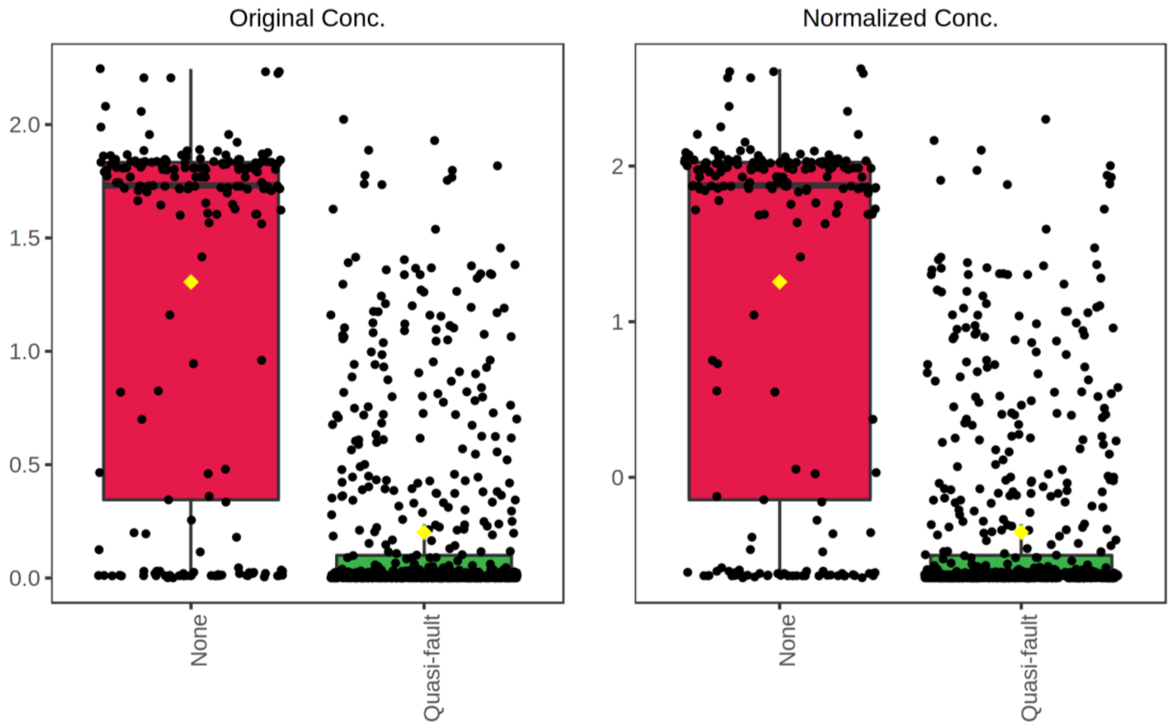


Figure 76. Box and whisker plot of N_1Q_CS at closing saddle position signal

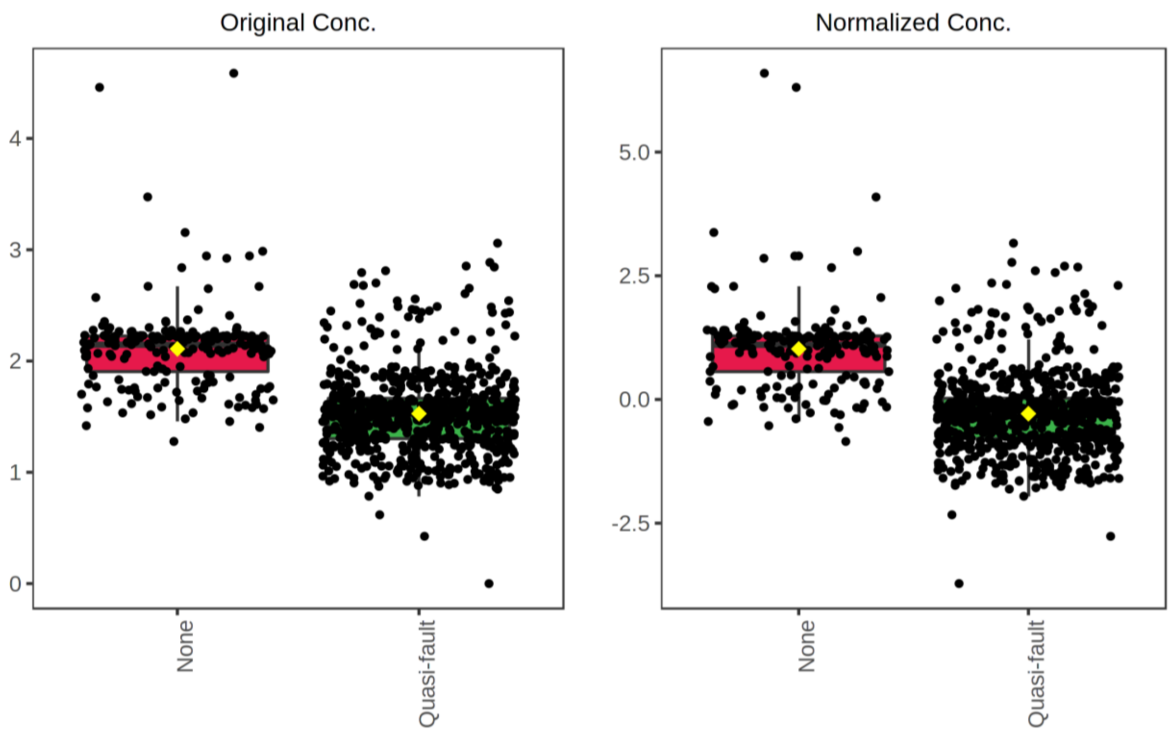


Figure 77. Box and whisker plot of N_Mean_CS at closing saddle position signal

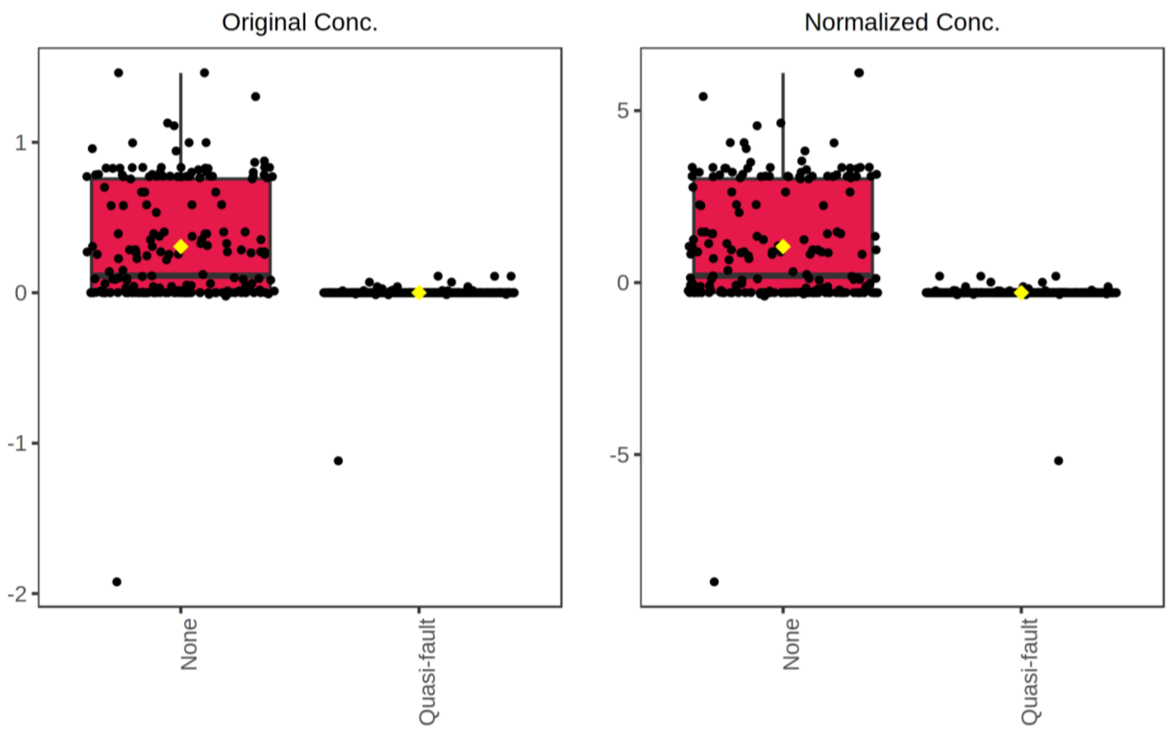


Figure 78. Box and whisker plot of N_min_CS at closing saddle position signal

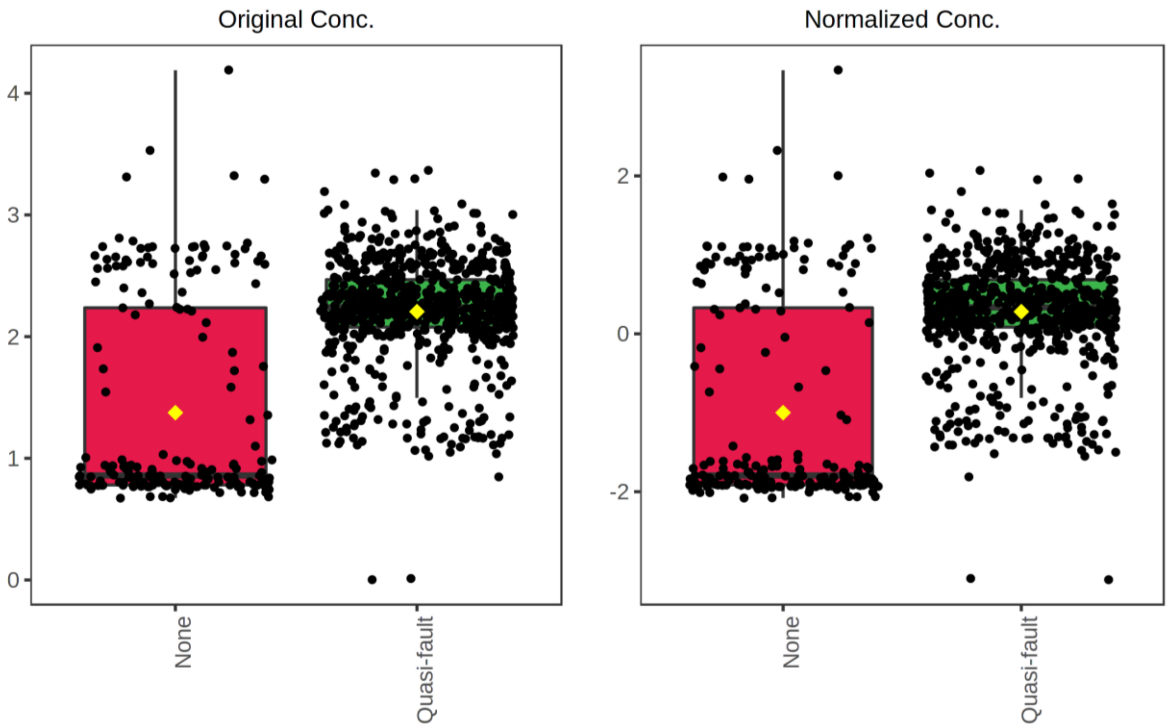


Figure 79. Box and whisker plot of N_IQR_CS at closing saddle position signal

Although not quite clear changes in different properties of signal data are observed from the previous figures, in addition, PCA will be used to do exploratory analysis regarding the normal and quasi-state of operating conditions, i.e., functional-productiveness considering the investigated PCs.

8.3 Principal Component Analysis (PCA) for data exploration

8.3.1 PCA of HyPower at opening saddle position

Investigating the relationship between hydraulic power (-energy) variables in diagnosing the state is additionally done through an investigation, i.e., data exploration via PCA. First, the features are standardised to avoid bias and error in estimation (Appendix 13) and then used for data visualisation. The results are depicted via PCA plots for the first five components (Figure 80). As it can be observed, the first five components explain 77.8% of data variation, with PC1 and PC2 for about 52.3% of the variation. The second step is to evaluate the PCA biplot (Figure 81) of suggested principal components for data exploration and re-check and compare with correlation heatmaps to determine the feature vectors. Additionally, a graphical representation of PCA components can be used to eliminate variables that impose multicollinearity on the prediction models or even eliminate outliers.

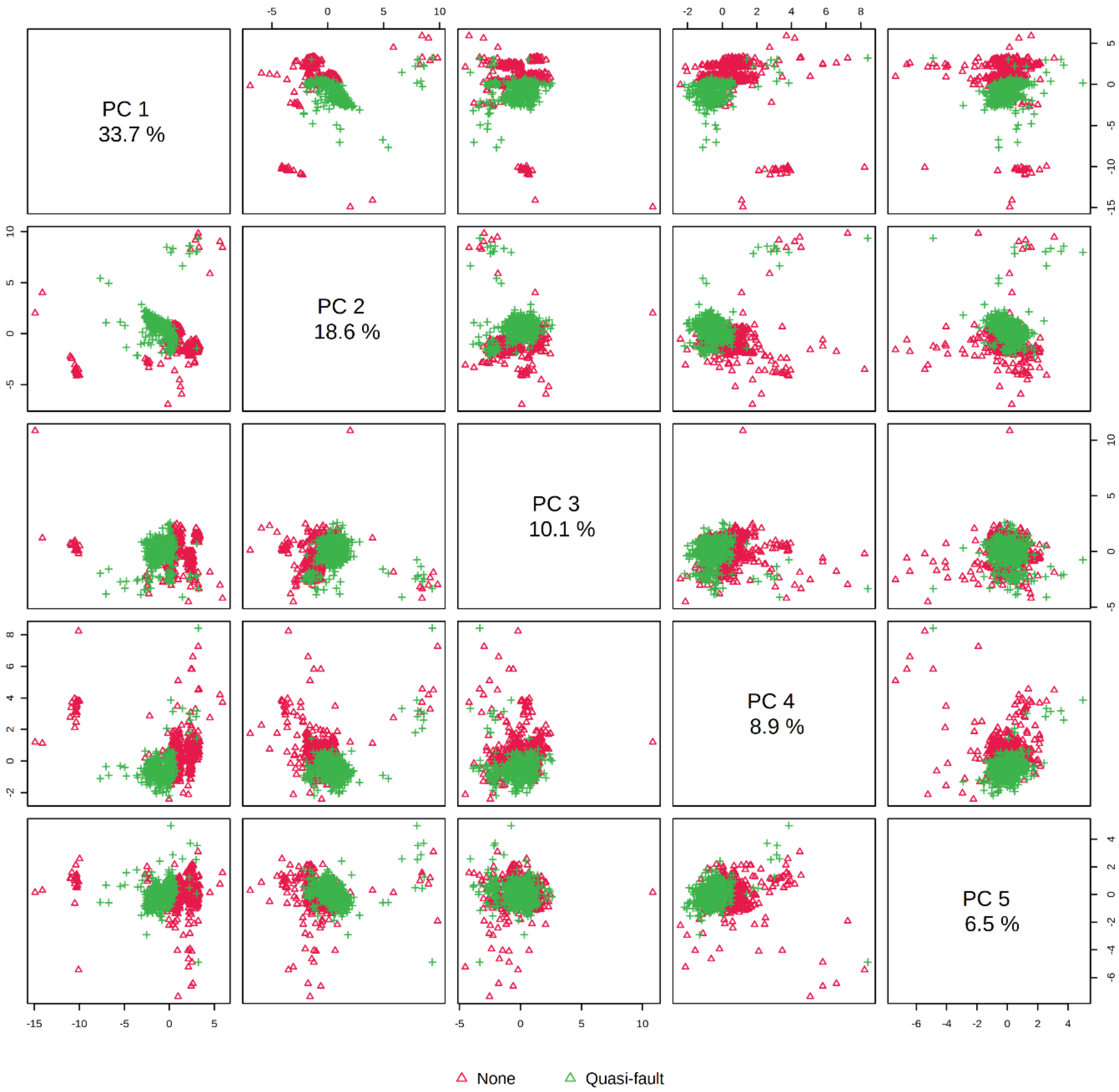


Figure 80. PCA results of the first five components for opening saddle

The PCA biplot represents the vector loadings (arrows) and scores (data points or samples) of two PCs (e.g., PC1 and PC2). Variables explained in the biplot are represented as vectors or arrows, while data points or sample identifiers represent the scores. The origin represents the average values of variables across sample points. As it can be observed, this origin has been centred (standardised), meaning that both PCs have an origin that is zero. The vector (arrow) length is directly proportional to the variability of the data included in two PCs. For instance, looking at T2 and HS_idle_time, these two loading vectors contain little information about elements in the first two PCs. The angle between variables indicates the correlation factor. If the angle between variables is close to 0°, it shows collinearity (e.g., N_RMS_OS, N_Mean_OS and N_Median_OS), which the analyst then needs to select one of the three variables (note: must be at the same direction) for avoiding the multicollinearity. Other instances include if the angle between vectors is 90°, it shows that both vectors are orthogonal, i.e., lack of or no correlation. The smaller the angle, the higher; therefore, the correlation is. If, however, the angle is between 90° and 180° (e.g., greater obtuse angle), then those variables are negatively correlated (e.g., 180° → r = -1) as in the case of N_1Q_OS and T2.

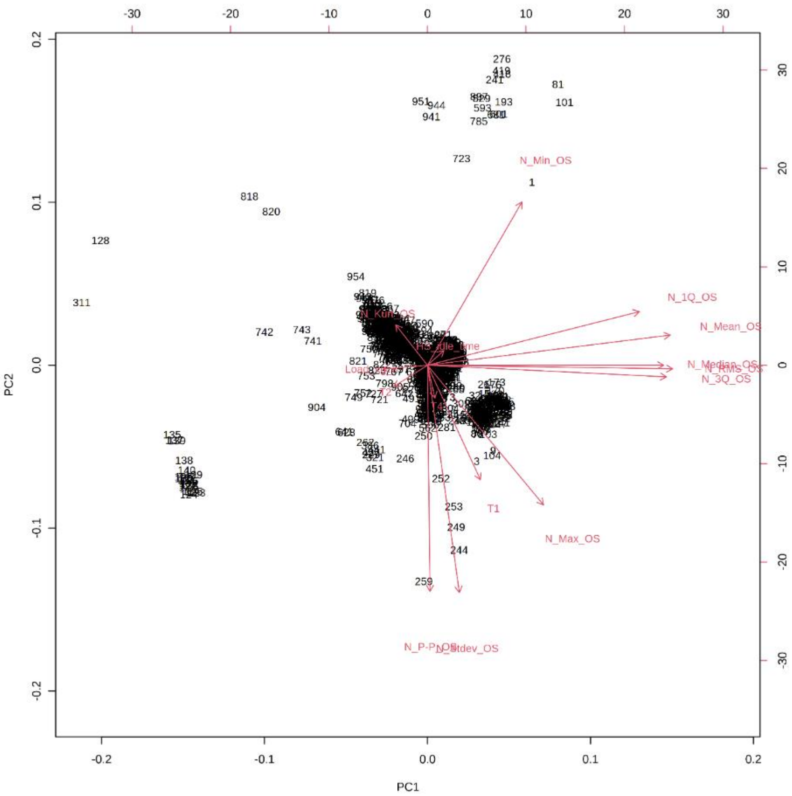


Figure 81. PCA biplot of PC1 and PC2 of hydraulic power data at opening saddle position

Hence, removing variables that induce multicollinearity to the features and sample data (N_RMS_OS, N_P-P_OS, N_Mean_OS, N_3Q_OS, N_1Q_OS), the selected variables are presented in Appendix 13 and used for ML model selection and validation. However, although the data with most of the variation is usually used for establishing and labelling, and in the case of unsupervised learning, used for separating and classification algorithms (e.g., k-Means clustering, Self-Organizing Maps). In this case, observation of PC1 and PC3 can provide better eigenvalues (Figure 83) for eigenvectors to be used for classification since they can be observed to have better discrimination ability than using the first two PCs (Figure 84) even though they provide more variation, i.e., information about the data from eigenvalues. However, although this thesis uses PCA for data visualisation and feature exploration, it will not be used for data processing, i.e., data extraction via Singular Value Decomposition (SVD). Thus, usage of standardised data and feature extraction and pre-processing will be a task of the future research articles and is beyond the scope of the thesis. The underlying reasons for not using PCA are explained briefly.

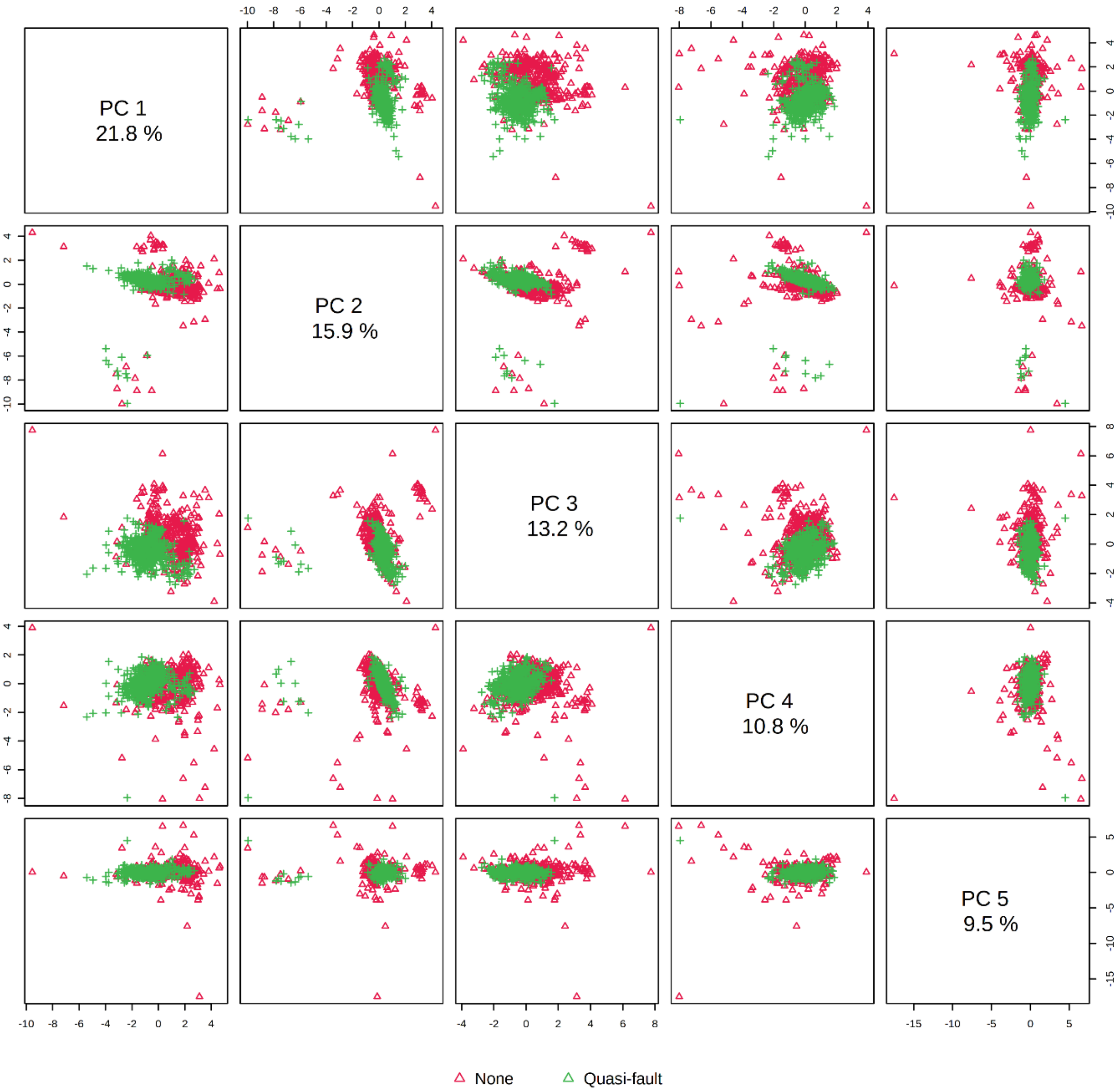


Figure 82. PCA overall plot after removing collinear variables

Several reasons support the decision not to use PCA. Firstly, loss of data variation (<80%) is because data samples and features are non-normally distributed; hence, PCA works on a linear basis of SVD is the most apparent one. That is to say; it measures the linear relationship between eigenvectors based on Pearson's correlation factor. Hence, since it is observed that there is an absence of linearity between variables, it thus requires more components to explain much of the data variation. To further justify the point, the case that we need as many as six components to explain 79,6% variation of data is difficult to use for classification since k-means are usually used for establishing centroids in the 2D vector space. Thus, we will lose as much as 62,3% of the information (if we consider that PC1 and PC2 explain only 37,7% of data variation). We can observe that PC1 and PC3 can be used with better discrimination ability than the first two components (Figure 84). Looking at the 3D plots of components (Figure 85) and their factor loadings (Figure 86), we can conclude that they are somewhat good discrimination, although with almost 50% loss of data information. During the writing of the thesis, t-SNE and UMAP non-linear dimension reduction techniques have emerged, although no papers on the maintenance of hydraulic systems have been reported and will be a part of future research studies.

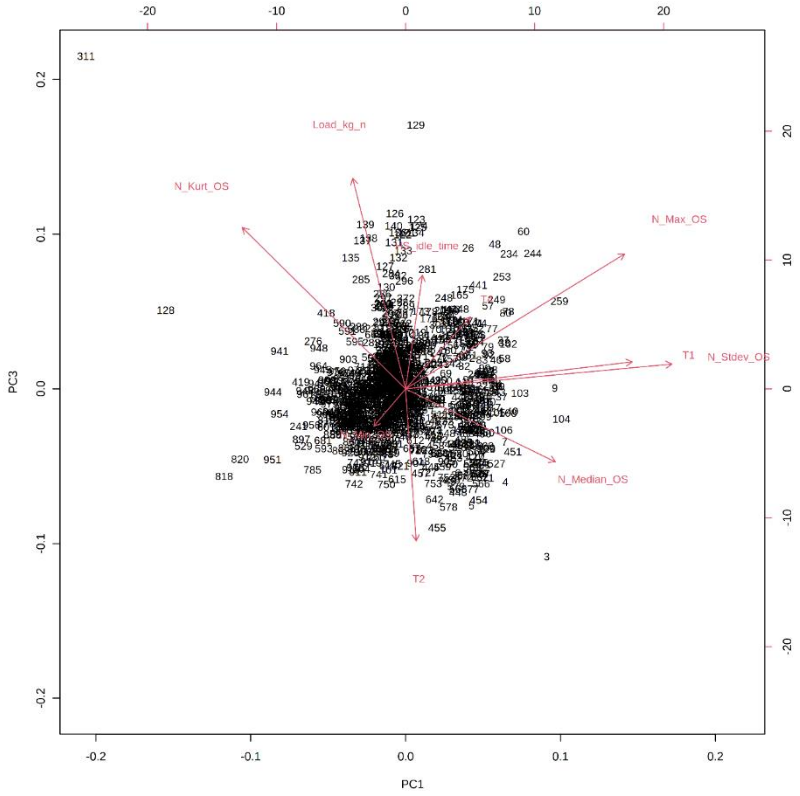


Figure 83. PCA Biplot for PC1 and PC3 data at opening saddle position

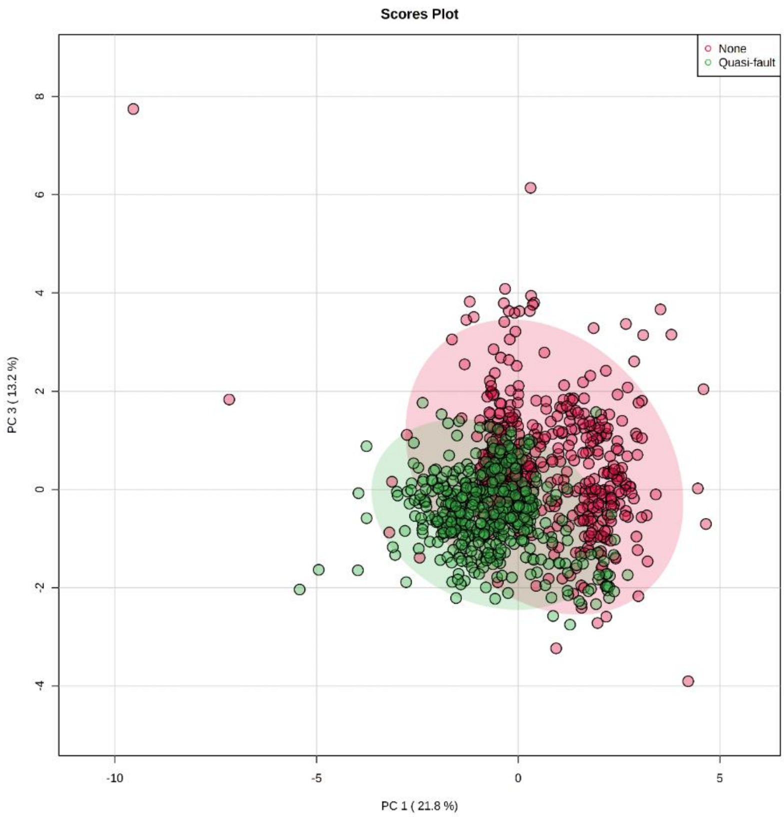


Figure 84. PCA plot of PC1 and PC3 components at opening saddle position

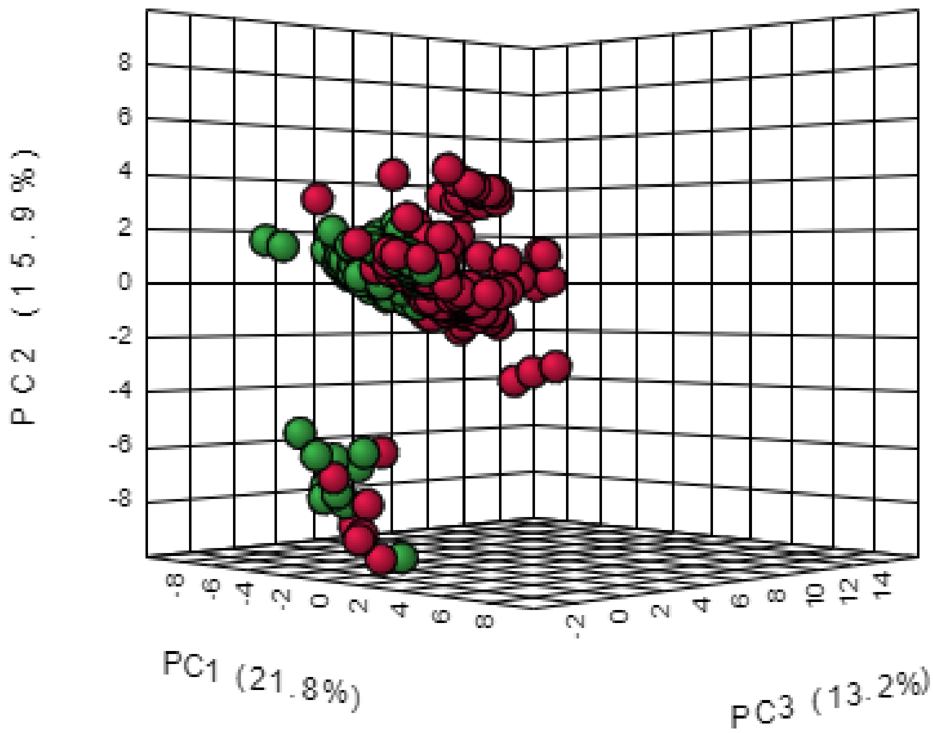


Figure 85. PCA 3D plot at opening saddle position

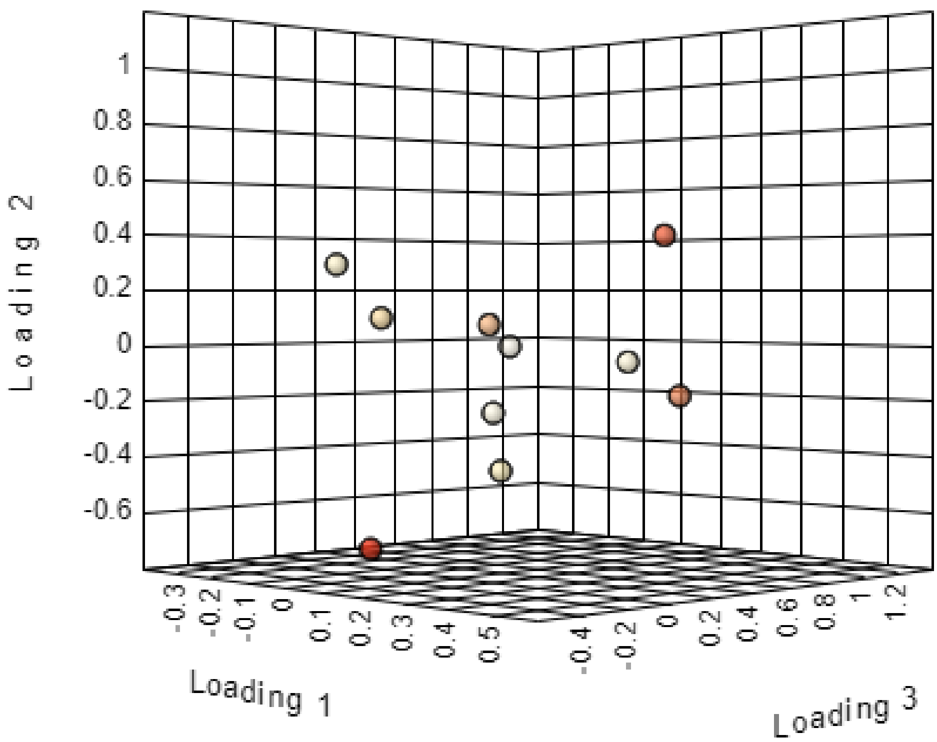


Figure 86. PCA 3D loadings plot at opening saddle position

8.3.2 PCA OF HYPOWER AT IDLE SADDLE POSITION

After using the correlation heatmap for feature selection and elimination, data exploration on idle_saddle position variables is used to check the presence of anomalies and potential data clustering. Namely, unlike opening saddle position data for the selection of data, it can be observed from an overall PCA plot that PC1 and any of the following components (PC2, PC3, PC4, PC5) can be used for classification since it provides good classification ability of healthy and unhealthy conditions, i.e., Normal and Quasi-failure condition as noted. In this particular state of idle saddle position, data can be used as an LDA (Linear Discriminant Analysis) algorithm, which is similar to PCA, however, with the ability for establishing classification and validation of results.

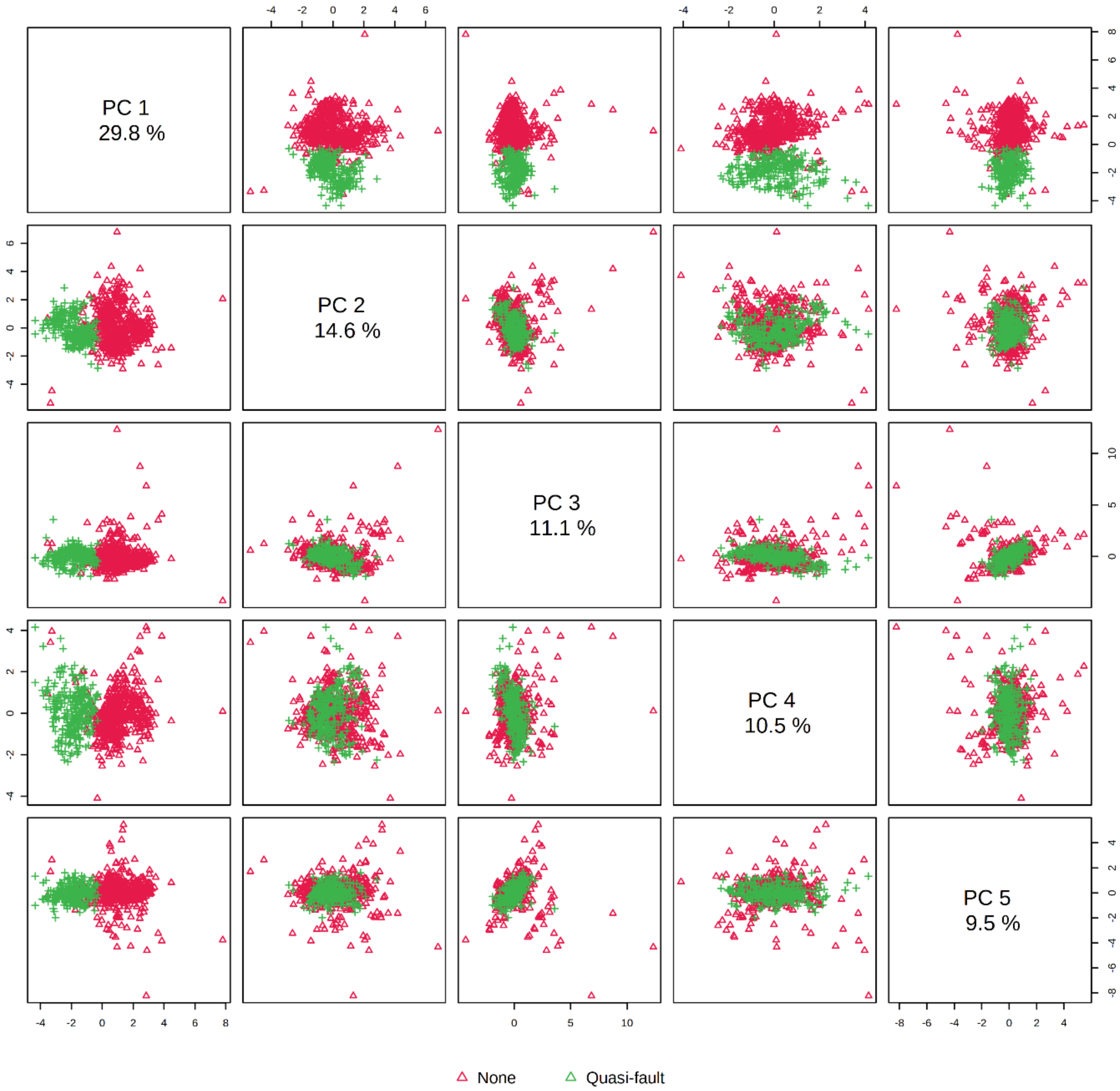


Figure 87. PCA overall plot of hydraulic power data at idle saddle position

Observing the PCA biplot of idle saddle position can be seen as low or no collinearity (Figure 88). In the following, it can be observed that the plot of the first two PCs shows almost excellent separating properties (Figure 89), and also with a 3D plot of data (Figure 90) and loadings (Figure 91). Although as stated, the point of feature exploration and visualisation for establishing important features and thus, the selection is the only task of PCA in this thesis.

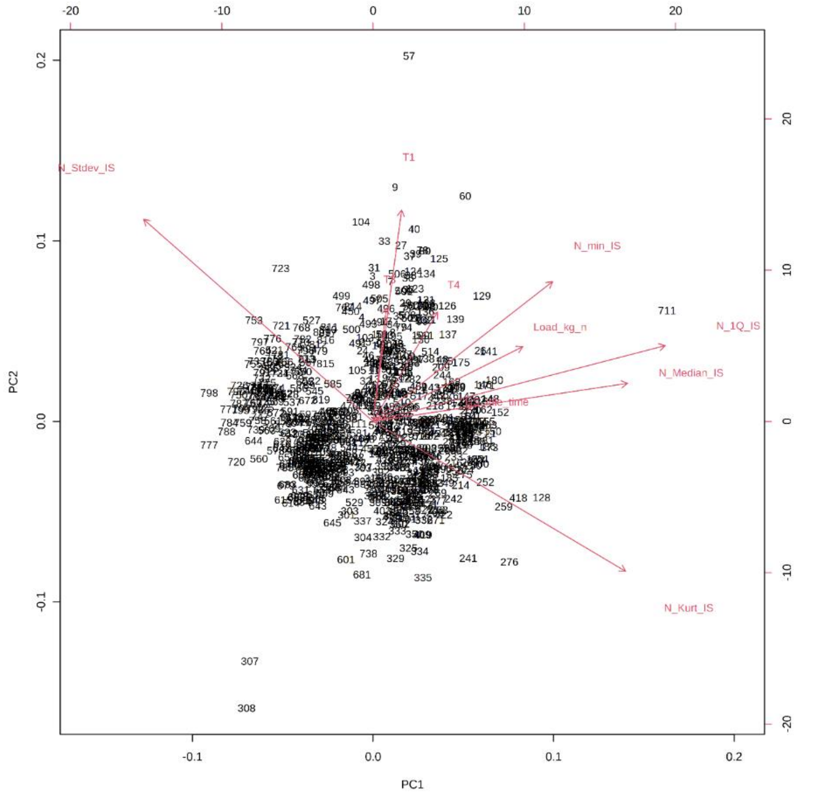


Figure 88. PCA Biplot of hydraulic power data at idle saddle position

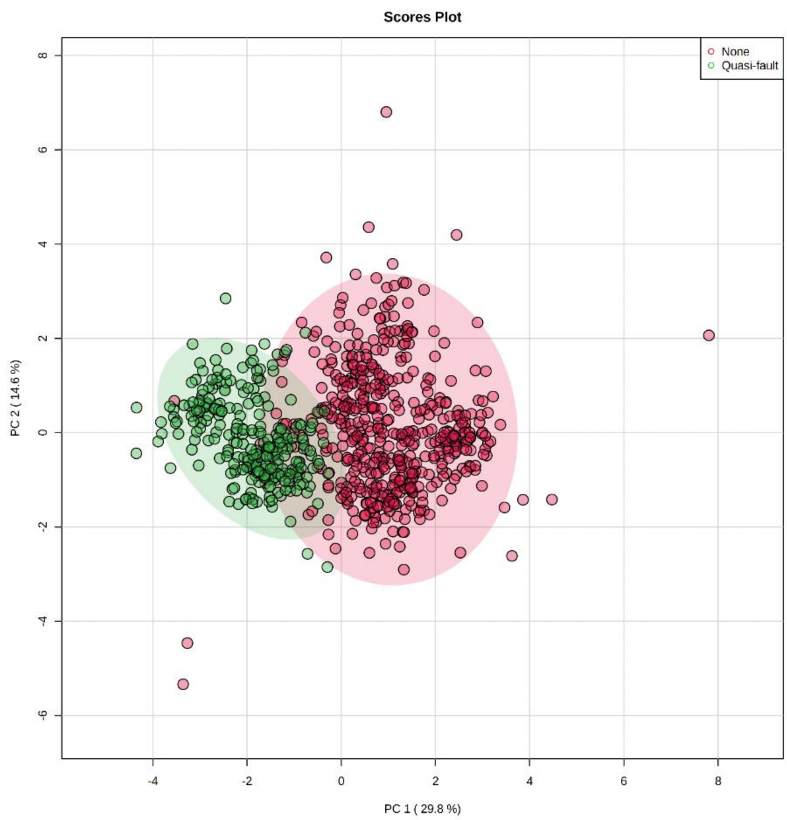


Figure 89. PCA plot of first two PCs of hydraulic power data at idle saddle position

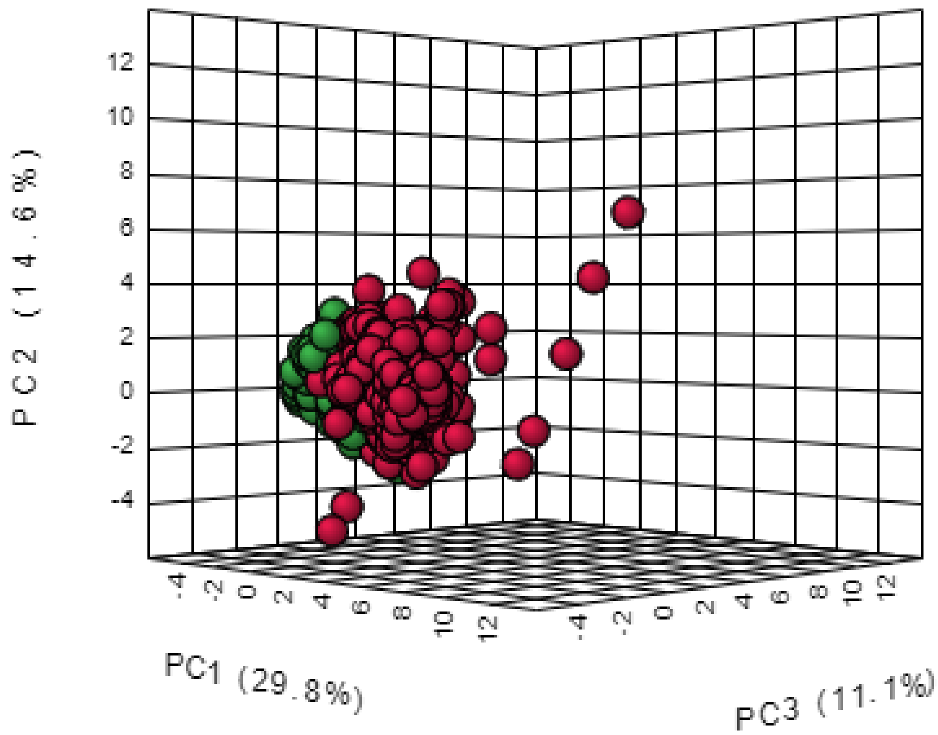


Figure 90. 3D plot of hydraulic power data at idle saddle position

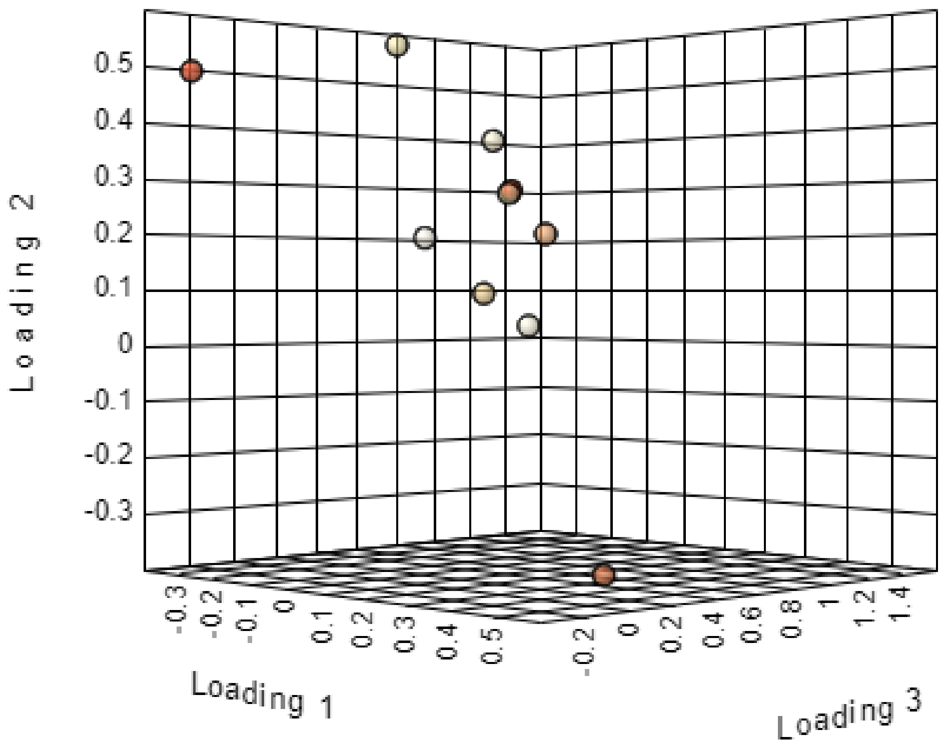


Figure 91. 3D plot of hydraulic power data loadings at idle saddle position

8.3.3 PCA of HyPower at closing saddle position

Observation of data from closing saddle position can be observed, as in the previous state, almost excellent separation, i.e., classification properties of features from a given sample. Namely, the first three components explain more than 90% of the data (Figure 92), showing the high presence of linearity between the variables, which can also be observed by the absence of multicollinearity in the biplot (Figure 93). Data exploration can also observe the low presence of deviation in the data and outliers. However, considering the previous samples and observation of closing saddle position, variables of saddle position (rotation speed) do not correlate with the variables.

It can also be observed from the PC1 and PC2 plots of data (Figure 94) good separation of system conditions. In addition, observing the 3D plot of data (Figure 95) and associated loadings (Figure 96) that the highest factor loadings explain the variation of hydraulic power variables (N_Mean_CS, N_RMS_CS, N_1Q_CS), while PC2 shows the information of deviation in the signal (N_StDev_CS). Hence, the PC1 explains the change in the "amplitude" of the HyPower variable, while the PC2 shows that variation in function.

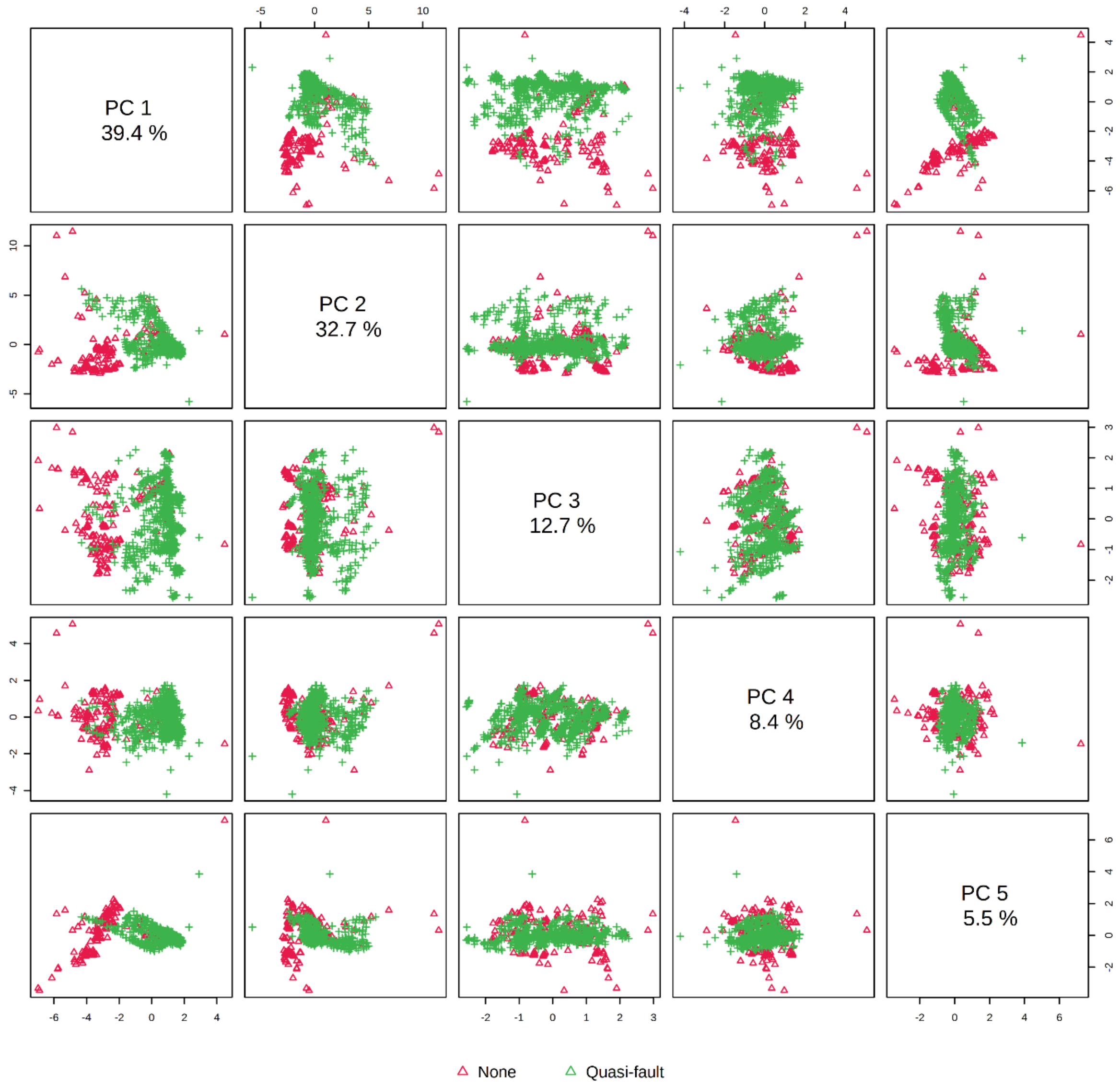


Figure 92. PCA overall plot of hydraulic power data at closing saddle position

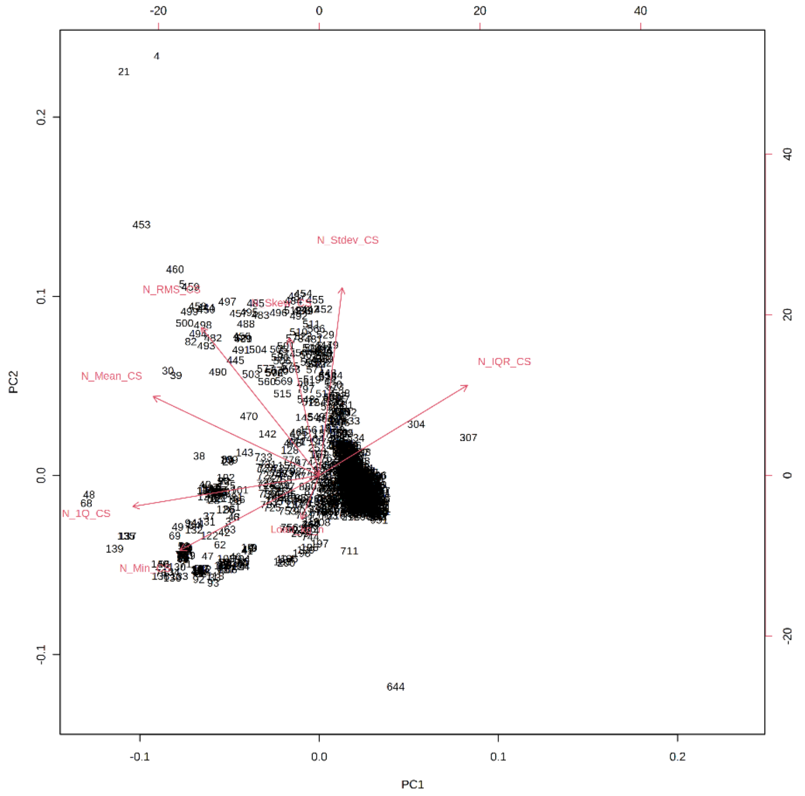


Figure 93. PCA Biplot of hydraulic power data at closing saddle position

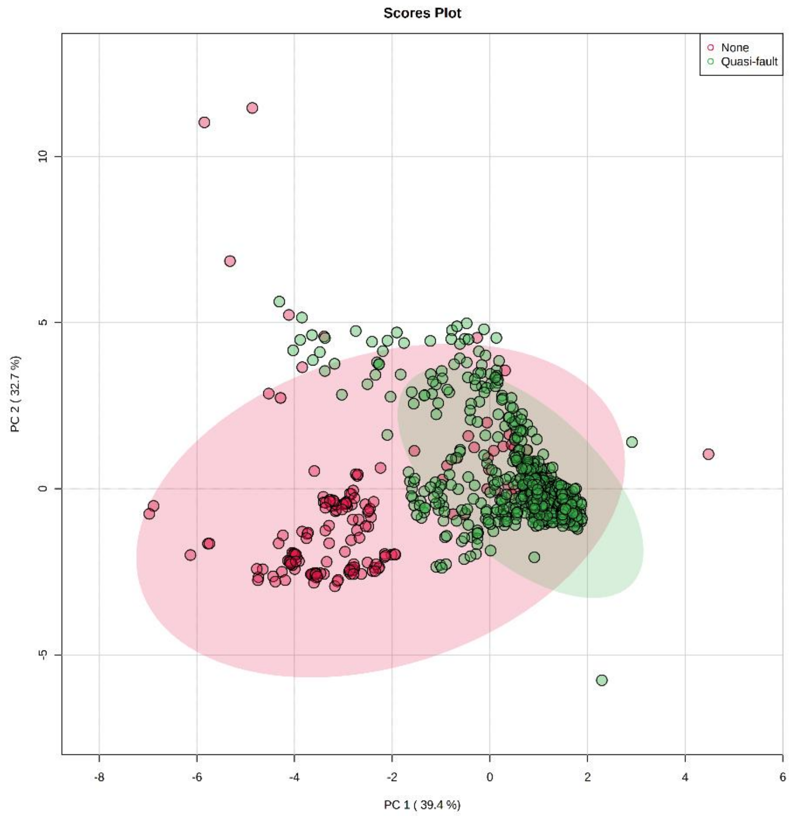


Figure 94. PC1 and PC2 score plot of hydraulic power data at closing saddle position

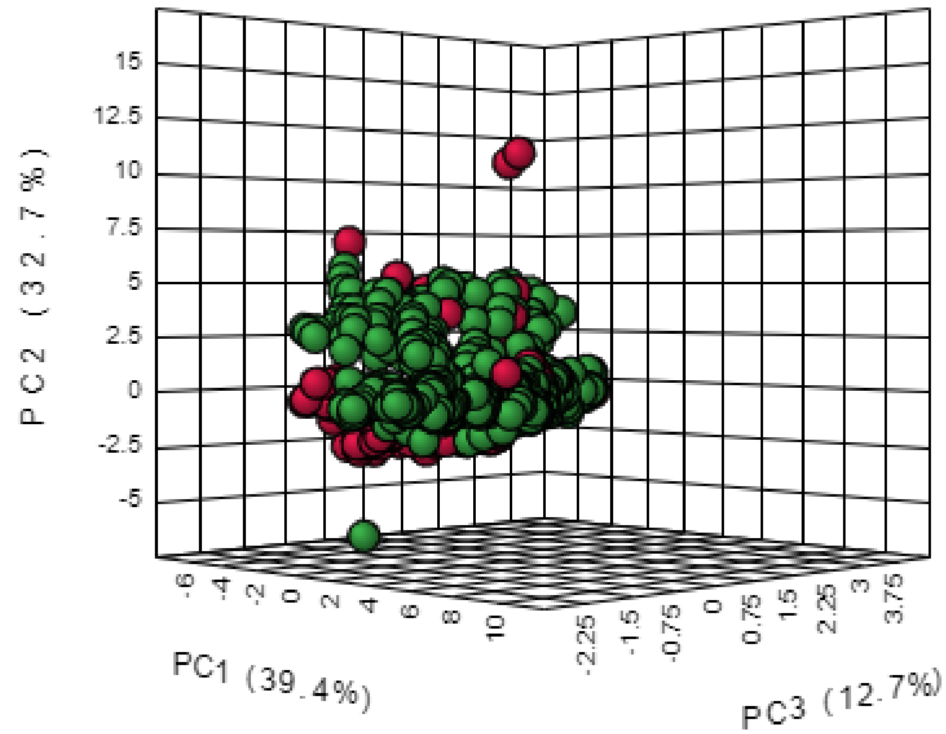


Figure 95. 3D PCA plot of hydraulic power data at closing saddle position

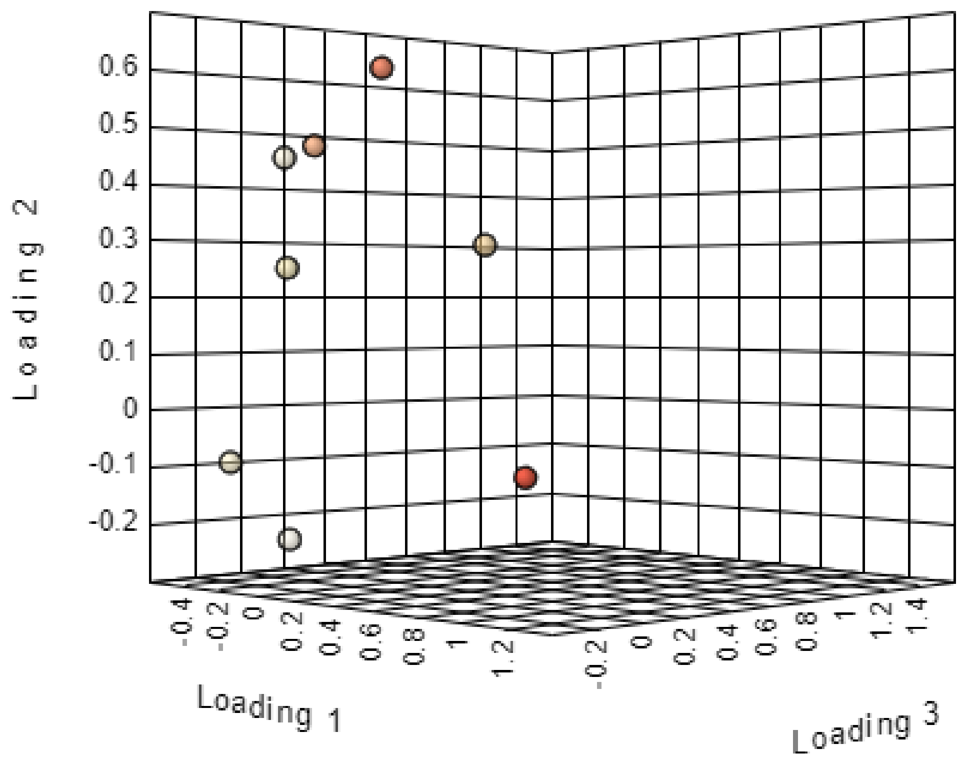


Figure 96. 3D PCA plot of hydraulic power data at closing saddle position

8.4 DATA SELECTION AND NORMALIZATION

The last stage of data pre-processing includes integrity check and normalisation. ***Data integrity/quality check's*** main aim is to deal with processes, in this case, the data containing many peaks, thus eliminating false positive peaks. Data containing outliers and false peaks can result in false positive or false negative classification results. Therefore, an appropriate variation reduction must be done for the data to be valid. For instance, data containing stoppages, i.e., total failure due to failures of components, are eliminated since it is obvious that the classification of that results cannot be wrongfully predicted.

Considering that thesis is dedicated to modelling appropriate dynamic deteriorating mechanisms, thus avoiding true positive misclassification, failures will not be used in the thesis. Since no data was detected in the opening saddle position, all samples were taken for analysis. At idle saddle position, however, 209 samples were eliminated since the prediction accuracy will presumably be maximum considering the known fact that total failure has occurred. At closing saddle position, 64 samples were eliminated since it has been known that the sensor for controlling saddle position is replaced at the time of recordings. This resulted in re-modelling the sensor time for dumping process mass, creating bias in the final estimation. Consequently, reducing false-negative results.

Data normalization (**scaling**) considers adjusting data to normality, i.e., ignoring the scale of a unit of measurement. That is to say, setting the samples to be oriented on a lower level scale. This procedure is usually important when variables are of different orders of magnitude. Usually, data standardization (8.9) is used to scale data or other methods like min-max, Pareto scaling, and range scaling. In this particular case, normalisation of data is done by standardising the dataset as:

$$x_{standardised} = \frac{x_i - \bar{x}}{\sigma} \tag{8.9}$$

No transformations of values (log or square root) are done. There is an important note when using data normalisation vs standardisation. It can be noted as data normalisation, whether transforming the data into a „Normalized dataset“ or „Standardised dataset“, both range values between 0 and 1. However, the standardised dataset will have a mean value of 0 and a standard deviation of 1, used here in the thesis. The dataset is standardised for all included features and saddle positions and is depicted in Appendix 13.

The data will be split into a training set (70%) and a testing set (30%). For testing the hypothesis within the machine learning realm, the parameter of **accuracy** is chosen for model selection. In addition, the classification (confusion) matrix for each model will be presented, with ROC and AUC for the point of discussion. In the following chapter 5 selected machine learning models are used as hypothesis space:

(1) Gaussian Naïve Bayes (GNB) for binary classification;
(2) Artificial Neural Network (ANN) binary classifier with one hidden layer;
(3) Classification and Regression Decision Tree (CART) for binary classification;
(4) Logistic Regression (LR) for binary classification;
(5) k-Nearest Neighbour (kNN) for binary classification.

9 MACHINE LEARNING MODELS

9.1 NAIVE BAYES CLASSIFIER FOR HYDRAULIC POWER DATA

Naive Bayes belongs to a group of "generative classification models". These models compute classifiers based on the joint probability density function *P*(*X, Y*) on set *X* and target label *Y*. On the other side, the discriminative approach or model is built upon the conditional probability *P*(*Y*|*X*=*x*) of the target *Y* given *x*. Typical examples of generative classifiers are naïve Bayes, LDA, and Boltzmann machines, while discriminative models are kNN, SVM, Decision Trees, Logistic Regression and other classifiers. The basic idea of the Bayes classifier is to minimize the probability of misclassification problems. Consider a dataset *X* and *Y* used for the classification problem, where *Y* is the classification problem labelled as binary value [0, 1] of *X*, is given as:

$$(X|Y = u) \sim P_u, u = 1, 2, \dots k. \tag{9.1}$$

P_u represents the probability distribution, and the symbol „~" is "distributed as". Hence, the classifier here is a rule that assigns an observation $X = x$ an estimate of an unobserved variable label $Y = u$. Theoretically, a classifier is a measured function denoted as:

$$C: \mathbb{R}^d \rightarrow \{1, 2, 3 \dots k\} \tag{9.2}$$

Where *C* is a classifier that classifies the point of *x* to class *C*(*x*), in addition, the probability of misclassification of *C* is defined as:

$$Pr(C) = P(C(x) \neq Y). \tag{9.3}$$

Therefore, the Bayes classifier is the maximum argument of a probability that a given input value *x* is classified accordingly to the label output *y* and is defined as:

$$C^{Bayes}(x) = \underset{u \epsilon \{1,2,\dots k\}}{\operatorname{argmax}} P(Y = u|X = x) \tag{9.4}$$

In a conditional probability model, Naïve Bayes is then represented by a vector $\mathbf{x} = \{x_1, x_2, \dots x_n\}$ consisting of *n* features (independent) with probabilities of $P(C_k| \ x_1, x_2, \dots x_n)$ for each possible outcome of class *C*. The problem is described as:

$$P(C_k|\mathbf{x}) = \frac{p(C_k)p(\mathbf{x}|C_k)}{p(\mathbf{x})}. \tag{9.5}$$

in simple terms, the model represents:

$$P\big(Y = y|\mathrm{X} = (x_1, x_2 \dots x_n)\big) = \frac{P(X|Y)P(Y)}{P(X)} = \frac{likelihood \cdot prior}{evidence}. \tag{9.6}$$

Given the equation, it can be understood that Naïve Bayes Classifier is Generative Learning Algorithm. This means that it learns from its prior probability. The prior probability is then calculated from the input features given known features as:

$$P(X) = P(X|Y_{n-1})P(Y_{n-1}) + P(X|Y_n)P(Y_n) \tag{9.7}$$

The discretisation of probability is done by transforming $\boldsymbol{x} \in (x_1, x_2 \dots x_n)$, where x_i is a continuous value of a variable in a given dataset *D*, into a new given categorical variable as group *G*. The second step includes fitting a known distribution (e.g. normal, Poisson) to given features:

$$P(\mathrm{X} = (x_1, x_2 \dots x_n)|Y = y) = \prod f(X_i = x_i|Y = y) \tag{9.8}$$

Where *Y* is considered a class of a given label (*y*), *f* denotes the probability density function of a known distribution, and the product sign $\prod$ is given considering that features are independent of each other.

9.1.1 GAUSSIAN NAÏVE BAYES CLASSIFIER FOR NUMERIC HYPOWER DATA

Since the Naïve Bayes classifier usually uses "naïve" probability of, usually, discrete values such as the probability of an event under a defined binary outcome [None; Quasi-fault], the probability of such discrete events is called **likelihood.** The most typical example of a naïve Bayes classifier usage is the classification of spam messages. However, since we are using continuous values, these probabilities are calculated by Bayes probability. Hence, it is called Gaussian Naïve Bayes (GNB). Since naïve Bayes under numeric values assumes Gaussian distribution, the training and testing set samples are assumed to be normally distributed. Therefore, it is considered a parametric ML model and works if training and testing data are normally distributed.

The GNB works by calculating each data point and assigning the point to the higher class probability that it belongs. An example of the classifier is shown in Figure 97 [131]. However, it should be duly noted that GNB **does not** use Euclidian distance in the sample (e.g., 2D scatter plot) but rather the distance from the Gaussian class label distribution mean and variance. Observing Figure 97, one can easily conclude that both classes [A, B] assume Gaussian normal distribution. Hence, it calculates the probability of a particular point x_i given the proposition that the same point (x_i) belongs to the specific class distribution. Hence, the goal is not to get the probability of a class, given the training data, but rather the probability of a class given the "new" test data.

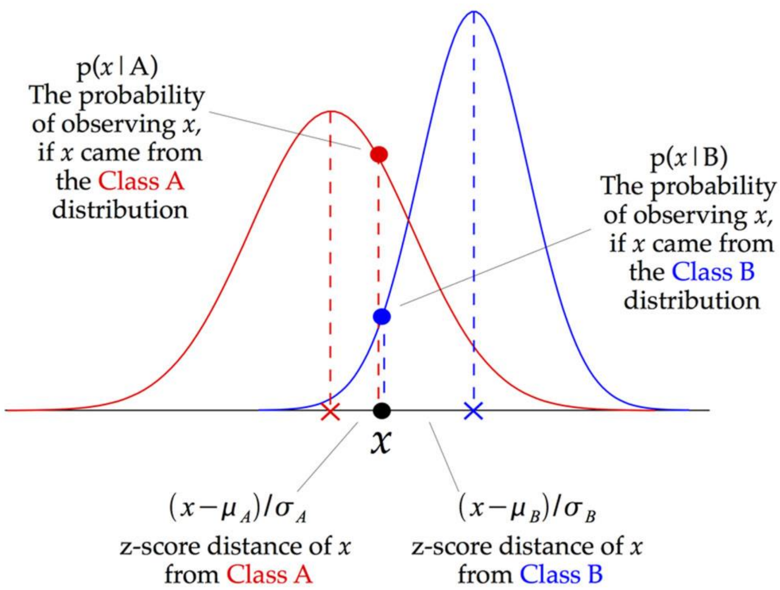


Figure 97. Gaussian Naïve Bayes (GNB) classifier graphical interpretation [131]

The Naïve Bayes starts with the probability of training data and only "thinks" that every possible probability is only under the constraints of training data and treats each input data as independent from the other. The naiveness in this case of opening saddle suggests that the model "thinks" that the possible outcome probability of binary events is equal to the training data size for both outcomes, 52% and 48% for None and Quasi-failure (Table 29), respectively. This probability is called ***prior probability***. Hence, the initial guess or prior probability of an event "None" is p(None) = 0.52.

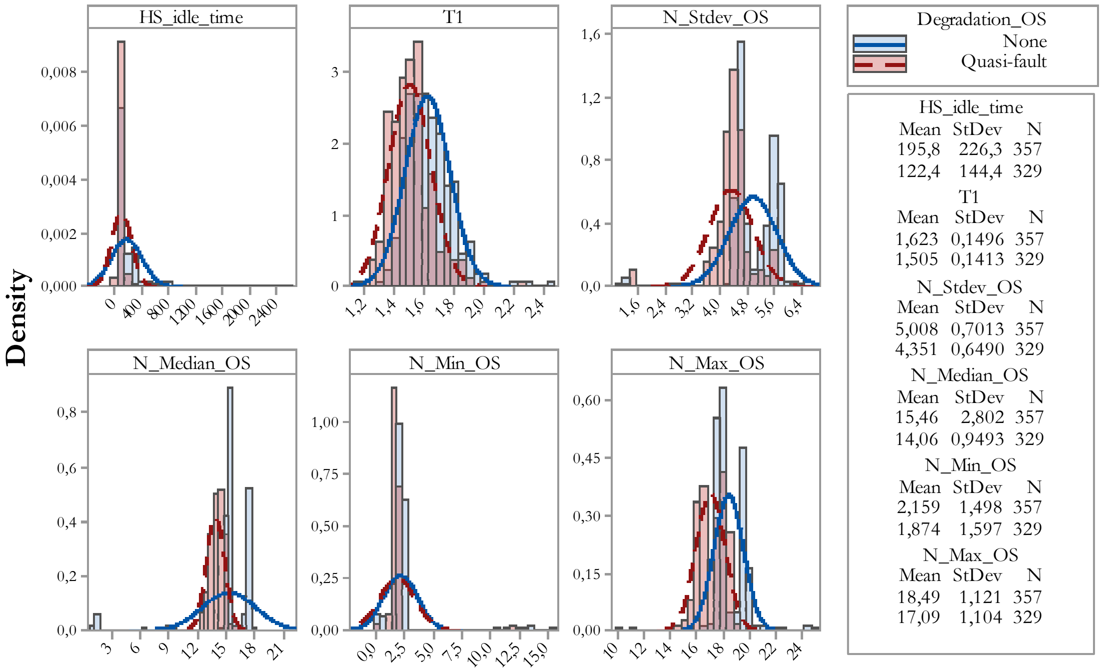


Figure 98. Histogram of opening saddle data given labels and descriptive statistics

Taking into account all of the associated features x_i under the prior probability of p(None):

$$P(\mathrm{X} = (x_1, x_2 \dots x_n)|Y = None) = \prod f(X_i = x_i|Y = None) \tag{9.9}$$

thus the equation would be:

$$p(x_i|y = None) = p(None) \cdot p(HS_{idle_{time}}|None) \cdot p(N\_T1\_OS|None) \cdot p(N\_T3\_OS|None) \cdot \dots \cdot p(N\_Kurt\_OS|None) \tag{9.10}$$

hence, we can technically express it as being proportional to the probability that an event is normal given the variables in the equation:

$$\big(p(None) \cdot p(x_i|None)\big) \propto p(None|x_i)\,. \tag{9.11}$$

However, since we assume Gaussian distribution and under such probability, we use numerical instead of categorical data (e.g., ordinal, nominal); we then must use the *likelihood estimation function* instead of probability. Therefore, using the likelihood ($\mathcal{L}$) estimate:

$$\mathcal{L}(\boldsymbol{X}|Y) = \aleph(\boldsymbol{X}|Y) = \aleph(\boldsymbol{X}|\mu, \Sigma) \tag{9.12}$$

where estimated parameters of both classifiers will need to be approximated as:

$$\begin{aligned} \mu_{MLE} &= \underset{\mu}{\operatorname{argmax}}\, \aleph(\boldsymbol{X}|\mu, \Sigma) \\ \Sigma_{MLE} &= \underset{\Sigma}{\operatorname{argmax}}\, \aleph(\boldsymbol{X}|\mu, \Sigma) \end{aligned} \tag{9.13}$$

thus, avoiding in-depth representation of best values of μ and Σ using calculus (partial derivatives) and putting in simple terms, the general representation of the MLE for mean and standard deviation under the Gaussian distribution assumption will be:

$$\mu_{MLE} = \frac{1}{N}\sum_{n=1}^{N} x_n\,;\ \sigma^2{}_{MLE} = \frac{1}{N}\sum_{n=1}^{N}(x_n - \mu)^2\ . \tag{9.14}$$

Inputting the into the equation (9.14) will give:

$$p(x_i|None) = p(None) \cdot \mathcal{L}(HS_{idle-time}|None) \cdot \mathcal{L}(T1|None) \cdot \mathcal{L}(T3|None) \cdot \dots \cdot \mathcal{L}(N\_Kurt\_OS|None) \tag{9.15}$$

where the likelihood function of a Gaussian distribution is:

$$\mathcal{L}(\mu, \sigma^2|x_1, x_2, \dots x_n) = \frac{1}{\sigma \cdot \sqrt{2\pi}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{9.16}$$

Hence, the higher probability of an estimate will return the class label.

9.1.2 GAUSSIAN NAÏVE BAYES ALGORITHM FOR OPENING SADDLE POSITION

The training data set (d_i) of a given dataset (D) is split into 70-30 as a rule of umb, i.e., training and testing; labelled data considers "None" operating conditions 52% of data and 48% of "Quasi-fault" or degradation-labelled data. All data is split as the stated proportion for training and testing data in Table 29. The proportion of classifiers or class labels as "None" and "Quasi-fault" is important since naïve Bayes starts with the prior probability and assumes the same probability for the testing data. Given the data class, the proportion of classifiers of randomly assigned sample data for training and testing could not be achieved with absolute equality of prior probability. However, each representation probability of class labels does not cross 2%, except in the opening saddle regime (Table 30). Besides, later in the analysis, disproportion (6.4%) shows lower prediction properties of class labels for every ML algorithm and will be a point of further investigation.

Table 29. Naïve Bayes Model Training Summary for Naïve Bayes classification algorithm

Properties		**n_OS**	**Percent**	**n_IS**	**Percemt**	**n_CS**	**Percent**
Operating state	None	357	52.0%	355	65.7%	128	20%
	Quasi-fault	329	48.0%	185	34.3%	512	80%
Valid		686	100.0%	540	100.0%	640	100.0%
Excluded		0	0%	0	0%	0	0%
Total		686	100.0%	540	100.0%	640	100.0%

Table 30. Naïve Bayes Model Testing Summary for Naïve Bayes classification algorithm

Properties		**n_OS**	**Percent**	**n_IS**	**Percemt**	**n_CS**	**Percent**
Operating state	None	159	54.1%	148	63.8%	73	26.4%
	Quasi-fault	135	45.9%	84	36.2%	203	73.6%
Valid		294	100.0%	232	100.0%	276	100.0%
Excluded		0	0%	0	0%	0	0%
Total		294	100.0%	232	100.0%	276	100.0%

Looking at Figure 99 and neglecting the presupposition that there are a non-significant proportion of "None" cases concerning "Quasi-failure" states (4% difference), the other thing is that we suspect not just from the previous data (e.g., Neural Network) that N_StDev_OS should be one of the most important indicators, aside from N_Median_OS, and N_Max_OS.

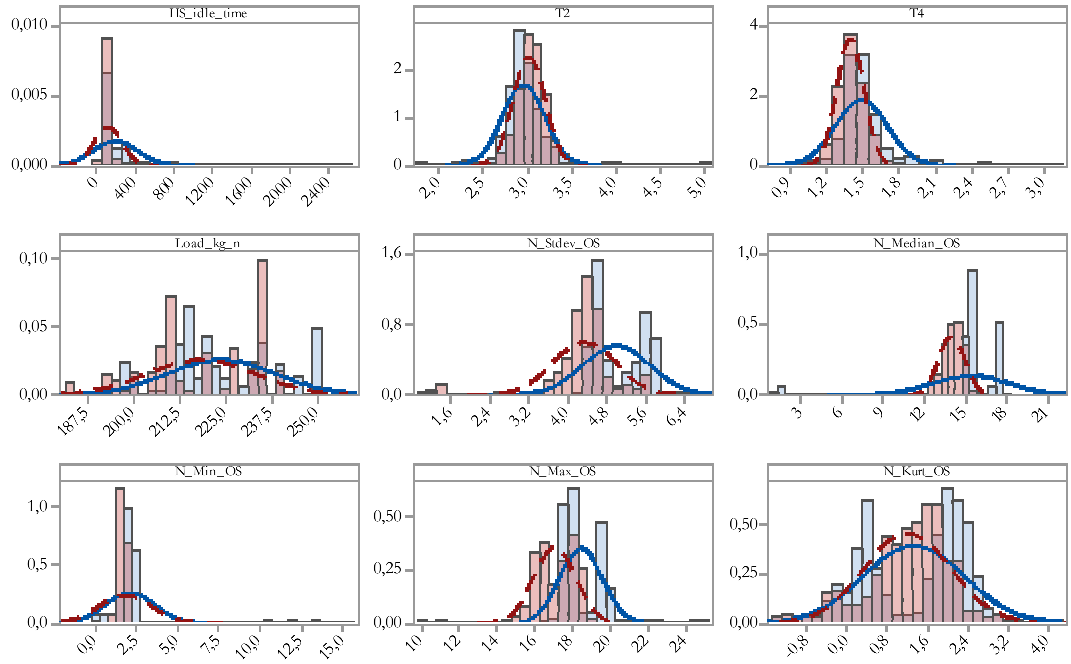


Figure 99. Histograms of training data predictors at opening saddle regime

The testing data also shows that the best separation can be achieved by looking at the N_StDev_OS, N_Median_OS and N_Max_OS. Checking the assumption will be done through the mathematical formulation of GNB. Firstly, we need to establish prior or conditional probabilities, and these probabilities are calculated from the sample or training dataset. Secondly, we need prior probabilities of Gaussian distribution of the sample dataset of each feature – mean and standard deviation. The calculations and the parameters for calculating probabilities and likelihoods of the testing sample are given in Table 31. The GNB takes the prior probabilities and likelihoods based on the training set's defined mean and standard deviation parameters. After collecting data from prior probabilities of None and Quasi-fault states of 52% and 48%, respectively, and parameters of Gaussian distribution (μ, σ^2), we can calculate the likelihoods of the measured parameter to the corresponding probabilities and assign the class of the testing sample points.

Table 31. Prior parameters of training dataset for opening saddle position

Training	Parameter	HS_idle	T1	T2	T4	Load	StDev	Med	Min	Max	Kurt
None	Mean	195.8	1.62	2.96	1.49	224.15	5.01	15.46	2.16	18.50	1.34
	St.Dev.	226.3	0.15	0.24	0.21	15.08	0.70	2.80	1.50	1.21	1.00
Q-fault	Mean	122.39	1.50	3.02	1.40	218.73	4.35	14.05	1.87	17.10	1.22
	St.Dev.	144.36	0.14	0.18	0.11	14.97	0.65	0.95	1.60	1.10	0.86

Representing the probability calculations given the prior probability and likelihood functions of first-class *None*:

$$\begin{aligned} p(x_{i-test}|None) = p(None|Training) \cdot \mathcal{L}(HS_{idle-time-test}|None) \cdot \mathcal{L}(T1_{test}|None) \\ \cdot \mathcal{L}(T2_{test}|None) \cdot \mathcal{L}(T4_{test}|None) \cdot \mathcal{L}(Load\_kg_{test}|None) \\ \cdot \mathcal{L}(N\_StDev\_OS_{test}|None) \cdot \mathcal{L}(N\_Median\_OS_{test}|None) \\ \cdot \mathcal{L}(N\_Min\_OS_{test}|None) \cdot \mathcal{L}(Max_{test}|None) \cdot \mathcal{L}(N\_Kurt\_OS_{test}|None) \end{aligned} \tag{9.17}$$

while also calculating the same probabilities and likelihoods of the "*Quasi-fault*" class label:

$$
\begin{aligned}
p(x_{i-test}|Quasi-fault) \\
&= p(Quasi-fault|Training)\cdot \mathcal{L}(HS_{idle-time-test}|Quasi-fault) \\
&\cdot \mathcal{L}(T1_{test}|Quasi-fault)\cdot \mathcal{L}(T2_{test}|Quasi-fault) \\
&\cdot \mathcal{L}(T4_{test}|Quasi-fault)\cdot \mathcal{L}(Load\_kg_{test}|Quasi-fault) \\
&\cdot \mathcal{L}(N\_StDev\_OS_{test}|Quasi-fault)\cdot \mathcal{L}(N\_Median\_OS_{test}|Quasi-fault) \\
&\cdot \mathcal{L}(N\_Min\_OS_{test}|Quasi-fault)\cdot \mathcal{L}(N\_Max\_OS_{test}|Quasi-fault) \\
&\cdot \mathcal{L}(N\_Kurt\_OS_{test}|Quasi-fault)
\end{aligned}
\tag{9.18}
$$

where likelihood values of variables assuming *None* state are given for variables:

$$
\begin{aligned}
\mathcal{L}\left(HS\_idle\_time_{test}|\mu_{HS\_idle\_time_{train}};\sigma^2_{HS\_idle\_time_{train}}\right) &= \frac{1}{15.04\cdot\sqrt{2\pi}}\cdot e^{-\frac{(38.33-195.8)^2}{2\cdot 226.3^2}} \\
&= 0.0013838
\end{aligned}
\tag{9.19}
$$

$$
\mathcal{L}\left(T1_{test}|\mu_{T1_{train}};\sigma^2_{T1_{train}}\right) = \frac{1}{0.3873\cdot\sqrt{2\pi}}\cdot e^{-\frac{(1.52-1.6234)^2}{2\cdot 0.1496^2}} = 2.1296 \tag{9.20}
$$

$$
\mathcal{L}\left(T2_{test}|\mu_{T2_{train}};\sigma^2_{T2_{train}}\right) = \frac{1}{0.4898\cdot\sqrt{2\pi}}\cdot e^{-\frac{(3.86-2.9591)^2}{2\cdot 0.2359^2}} = 0.00115 \tag{9.21}
$$

$$
\mathcal{L}\left(T4_{test}|\mu_{T4_{train}};\sigma^2_{T4_{train}}\right) = \frac{1}{0.4583\cdot\sqrt{2\pi}}\cdot e^{-\frac{(1.46-1.4939)^2}{2\cdot 0.2112^2}} = 1.8647 \tag{9.22}
$$

$$
\mathcal{L}\left(Load\_kg_{test}|\mu_{Load\_kg_{train}};\sigma^2_{Load\_kg_{train}}\right) = \frac{1}{3.8833\cdot\sqrt{2\pi}}\cdot e^{-\frac{(198.71-224.15)^2}{2\cdot 15.08^2}} = 0.0064 \tag{9.23}
$$

$$
\mathcal{L}\left(N\_StDev\_OS_{test}|\mu_{N\_StDev\_OS_{train}};\sigma^2_{N\_StDev\_OS_{train}}\right) = \frac{1}{0.8366\cdot\sqrt{2\pi}}\cdot e^{-\frac{(5.328-5.0077)^2}{2\cdot 0.7013^2}} = 0.5125 \tag{9.24}
$$

$$
\mathcal{L}\left(N\_Median\_OS_{test}|\mu_{N\_Median\_OS_{train}};\sigma^2_{N\_Median\_OS_{train}}\right) = \frac{1}{1.6733\cdot\sqrt{2\pi}}\cdot e^{-\frac{(14.97-15.456)^2}{2\cdot 2.802^2}} = 0.14 \tag{9.25}
$$

$$
\mathcal{L}\left(N\_Min\_OS_{test}|\mu_{N\_Min\_OS_{train}};\sigma^2_{N\_Min\_OS_{train}}\right) = \frac{1}{1.2247\cdot\sqrt{2\pi}}\cdot e^{-\frac{(2.207-2.1592)^2}{2\cdot 1.4976^2}} = 0.2662 \tag{9.26}
$$

$$
\mathcal{L}\left(N\_Max\_OS_{test}|\mu_{N\_Max\_OS_{train}};\sigma^2_{N\_Max\_OS_{train}}\right) = \frac{1}{1.1\cdot\sqrt{2\pi}}\cdot e^{-\frac{(17.719-18.49)^2}{2\cdot 1.121^2}} = 0.2810 \tag{9.27}
$$

$$
\mathcal{L}\left(N\_Kurt\_OS_{test}|\mu_{N\_Kurt\_OS_{train}};\sigma^2_{N\_Kurt\_OS_{train}}\right) = \frac{1}{1\cdot\sqrt{2\pi}}\cdot e^{-\frac{(0.006-1.3435)^2}{2\cdot 0.9996^2}} = 0.1630 \tag{9.28}
$$

and finally, inputting that into eq (9.17) of product function, we get:

$$
\begin{aligned}
P(\mathrm{X}=(x_1,x_2\ldots x_n)|None) &= \prod p(None|None_{train})\cdot \mathcal{L}(x_i|None_{train}) \\
&= 1.83E-11
\end{aligned}
\tag{9.29}
$$

doing the same mathematical formulation for the training data assuming a “Quasi-fault” state, we get:

$$
\begin{aligned}
P(\mathrm{X}=(x_1,x_2\ldots x_n)|Quasi-fault_{train}) \\
&= \prod p\left(Quasi-fault\middle|Quasi-fault_{train}\right) \\
&\cdot \mathcal{L}\left(x_i|Quasi-fault_{training}\right) = 2.05E-12
\end{aligned}
\tag{9.30}
$$

Therefore, since there is a higher probability eq.(9.29), we assign the class label “None”.

After estimating the parameters and getting the results for classification, the final results are given in Table 32. As it can be observed, the classification of disturbances, i.e., Quasi-fault state-provided good prediction properties of training (92%) and testing (87%) data. However, observing the normal operating state without disturbances, i.e. “None” state, showed poor prediction properties than the degradational “Quasi-fault” state. Since naïve Bayes formulation works on comparing higher probability in determining class labels assuming Gaussian distribution, data seems not to follow the distribution assumption. Hence, one of the reasons is that machine learning classification models need to be tested using non-parametric assumptions of included parameters.

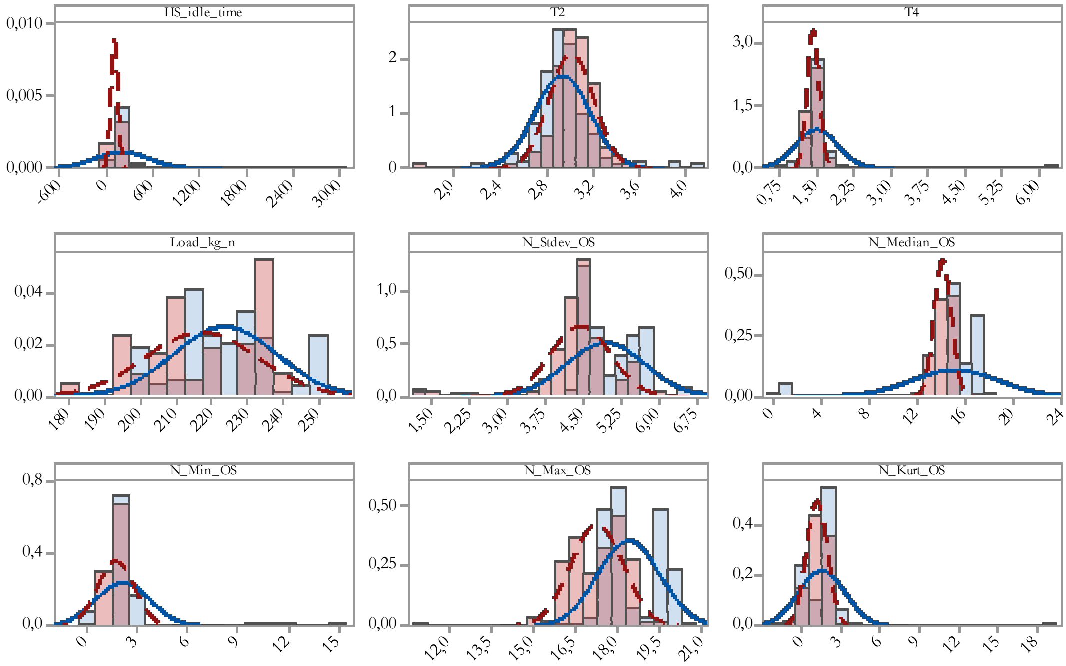


Figure 100. Histograms of testing data predictors at opening saddle regime

Moreover, observing the data from the testing set, it can be seen the difference in N_Max_OS and N_StDev_OS, which would be good for classification properties; however, since many data points within training data show some extreme values (considering that it showed “peaks” in hydraulic power regime (opening saddle) that may be caused by the inaccurate readings from the instruments, disturbances, or false readings, the N_Max_OS value showed the highest variable importance factor when determining class labels. At the same time, presumably standard deviation, i.e. N_StDev_OS predictor, also showed 2nd highest importance here but did not as much influence the results for making false positive or false negative predictions as the N_Max_OS predictor did. Therefore, training and testing will be conducted on the variables outside the Gaussian probability assumption.

Table 32. Naïve Bayes classification matrix score for opening saddle position

Sample	Observed	Predicted None	Predicted Quasi-fault	Percent Correct
Training	None	229	128	64.1%
	Quasi-fault	26	303	92.1%
	Overall Percent	37.17%	62.83%	**77.5%**
Test	None	104	55	65.4%
	Quasi-fault	18	117	86.7%
	Overall Percent	33.0%	67.0%	**75.2%**

9.2 ARTIFICIAL NEURAL NETWORK CLASSIFICATION MODEL

Artificial Neural Networks (ANNs) are familiar mathematical-statistical computational models used for prediction, either for regression (single value output) or for classification (discrimination). The ANN contains the building blocks of **nodes** and **connections** between nodes (Figure 101). Nodes and connections represent an intuitive illustration of how ANN transforms inputs to outputs through **hidden layers.** Hence, inputs given to neural networks are called **input layers** (x); transformation to outputs or **output layers** (y) are done via formulation and calculation through weights (W) and biases (b). Those weighted sums of input values and their associated bias are transformed via **activation functions** (f). Some of the basic mathematical notations in ANN usually contain, but are not limited to [132], [133]:

- m: the size of the sample in a given dataset of machine learning (training or testing);
- $n_{x,y}$: input size of x values; or output size for y values;
- $n_h^{[l]}$: number of units in a hidden l^{th} layer.
- $X \in \mathbb{R}^{n_x \cdot m}$: input matrix of n size of x values and m the sample size;
- $x^{(i)} \in \mathbb{R}^{n_x}$: i^{th} column vector example;
- $Y \in \mathbb{R}^{n_y \cdot m}$: is the label matrix;
- $y^{(i)} \in \mathbb{R}^{n_y}$: output label of the i^{th} example;
- $W^{[l]} \in \mathbb{R}^{n_y}$: weight matrix of the l^{th} layer;
- $b^{[l]} \in \mathbb{R}$: bias vector of the l^{th} layer;
- $y_i^{predicted}$: predicted output vector.

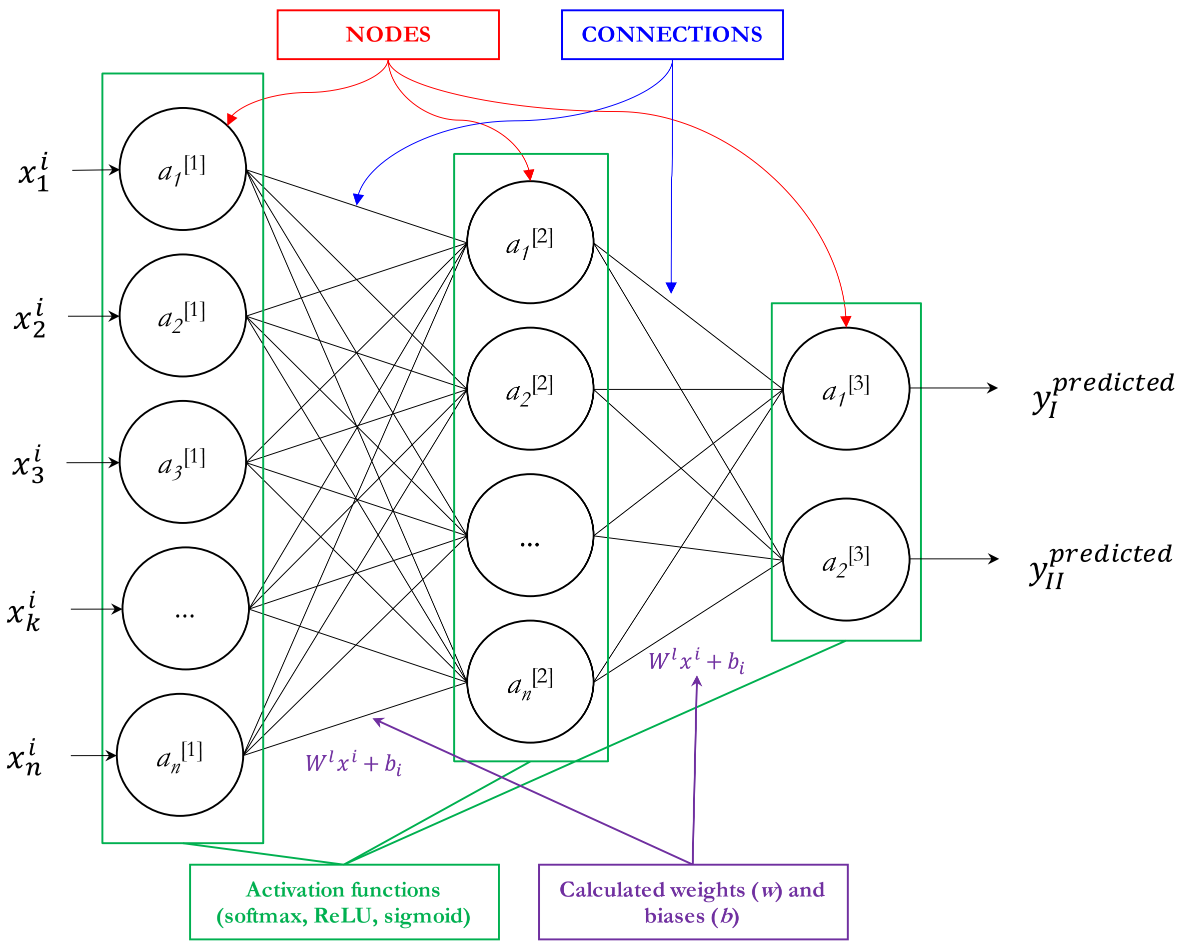


Figure 101. Artificial Neural Network conceptual explanation for binary classification model

The activation function is one of the most important components of a neural network. A neural network is developed based on human learning mechanisms (mimicking brain learning), so the activation function is built on a similar process from a single computational unit. The learning phase begins by receiving a stimulus from an environment (inputted values), processing the input data, and activating function maps or generating output values. The general forward propagation equation for calculating value at nodes is given as:

$$a = f^{[l]}\left(W_x \cdot x^i + b_i\right) \tag{9.31}$$

where $f^{[l]}(x)$ denotes the l^{th} layer activation function; thus, if $f^{[l]}$ is a sigmoid function (similar logistic regression), then the activation function of a given formula would be:

$$y^i = f\left(W_x \cdot x^i + b_i\right) \tag{9.32}$$

where f function, in this case, is sigmoid activation function is given as:

$$sigmoid(x) = f(x) = \frac{e^x}{e^x+1} = \frac{e^{(W_x \cdot x^i + b_i)}}{e^{(W_x \cdot x^i + b_i)}+1}\,. \tag{9.33}$$

Therefore, the activation function for a first is given as:

$$a_j^l = f^{[l]}\left(\Sigma_k w_{jk}^{[l]} a_k^{[l-1]} + b_j^{[l]}\right) = f^{[l]}\left(z_j^{[l]}\right). \tag{9.34}$$

where J (x, w, b, y) represent the cost function (bias estimate), and typically the cost function is given as entropy for optimising the performance of ANN as:

$$J(y^{pred}, y) = -\sum_{i=0}^{m} y^{(i)} log\left(y^{pred(i)}\right). \tag{9.35}$$

Since the thesis uses supervised machine learning simple ANN, Deep learning ANN (DNN) will not be further analyzed since it is beyond the scope of the thesis. In addition, the ANN prediction is used on a binary classification problem with one hidden layer. However, future research studies of the author will be dedicated to the deep neural networks with multiple hidden layers for multiple classification problems of quasi-faults in hydraulic systems monitoring and comparing energy-based maintenance parameters and other condition monitoring techniques (from the *p-f* curve). The following sub-section provides a practical research problem considering features from data pre-processing used for ANN classification problems.

9.2.1 ARTIFICIAL NEURAL NETWORK FOR OPENING SADDLE POSITION

Opening saddle position data is divided into 70/30 proportion, i.e., training and testing (Table 33), since there were no missing values nor biased data as in the case for closing and idle saddle position (e.g., replacement of sensors) that could potentially cause estimation bias and inaccuracy in prediction properties, the full data set is used.

Table 33. Model summary for opening saddle position

Data		**n**	**Proportion**
Sample	Training	686	70.0%
	Testing	294	30.0%
Total		980	

All of the input layer data and ANN component models, including many hidden layers, units, type of activation function for the hidden layer and all of the associated variables and parameters for the output layer, are given in Table 34.

Table 34. Neural network information and parameters for opening saddle position

Layers information	Covariates and data	Value	Explanation
Input Layer	Covariates	1	T1
		2	T2
		3	T4
		4	Load_kg_n
		5	N_Stdev_OS
		6	N_Median_OS
		7	N_Min_OS
		8	N_Max_OS
		9	N_Kurt_OS
		10	HS_idle_time
	Number of Units[a]		10
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		7
	Activation Function		Sigmoid
Output Layer	Dependent Variables	1	Degradation_OS
	Number of Units		2
	Activation Function		Sigmoid
	Error Function		Sum of Squares

a. Excluding the bias unit

The training model summary, including computational time and the sum of squared errors (SSE), is given in Table 35. The training model parameters and activation function are saved for testing the model on 30% randomly assigned test values.

Table 35. Training Model summary for opening saddle position

Training	Sum of Squares Error	7.547
	Percent Incorrect Predictions	1.0%
	Stopping Rule Used	Relative change in training error criterion (0.0001) achieved
	Training Time	0:00:00.04

Dependent Variable: Degradation_OS

The values of associated weights of given parameters in the training model and the bias value are given in Table 36. The weights and biases are used to test the model prediction properties. The complete look of a neural network is given in Figure 102.

Table 36. Training parameter estimates for opening saddle position

Predictor		**Predicted**								
		Hidden Layer 1							**Output Layer**	
		H(1:1)	**H(1:2)**	**H(1:3)**	**H(1:4)**	**H(1:5)**	**H(1:6)**	**H(1:7)**	**None**	**Quasi-fault**
Input Layer	(Bias)	-3.290	-.519	1.945	-1.212	-.090	-.058	-2.890		
	HS_idle_time	3.038	-.175	.809	-1.047	-.022	-.274	2.739		
	T1	.665	-.911	.034	.737	1.216	.976	2.568		
	T2	-.891	.346	-.353	-.519	-.881	-.936	-.743		
	T4	.974	-.371	.757	.868	.620	.126	.807		
	Load_kg_n	2.312	-.255	1.768	3.268	.584	.473	2.207		
	N_Stdev_OS	2.829	-4.305	7.294	-6.247	.519	.293	4.243		
	N_Median_OS	.961	-6.446	1.045	-.543	1.102	1.641	1.765		
	N_Min_OS	3.615	-2.550	4.999	.791	-.282	-.416	1.350		
	N_Max_OS	3.423	-.613	-2.822	-2.839	2.735	5.480	3.010		
	N_Kurt_OS	-.418	-.801	3.802	-1.035	-.406	-.647	1.933		
Hidden Layer	(Bias)								-.624	.434
	H(1:1)								4.475	-4.339
	H(1:2)								-5.210	5.233
	H(1:3)								7.935	-7.871
	H(1:4)								-5.241	5.327
	H(1:5)								-1.215	.885
	H(1:6)								-2.909	3.273
	H(1:7)								3.885	-3.933

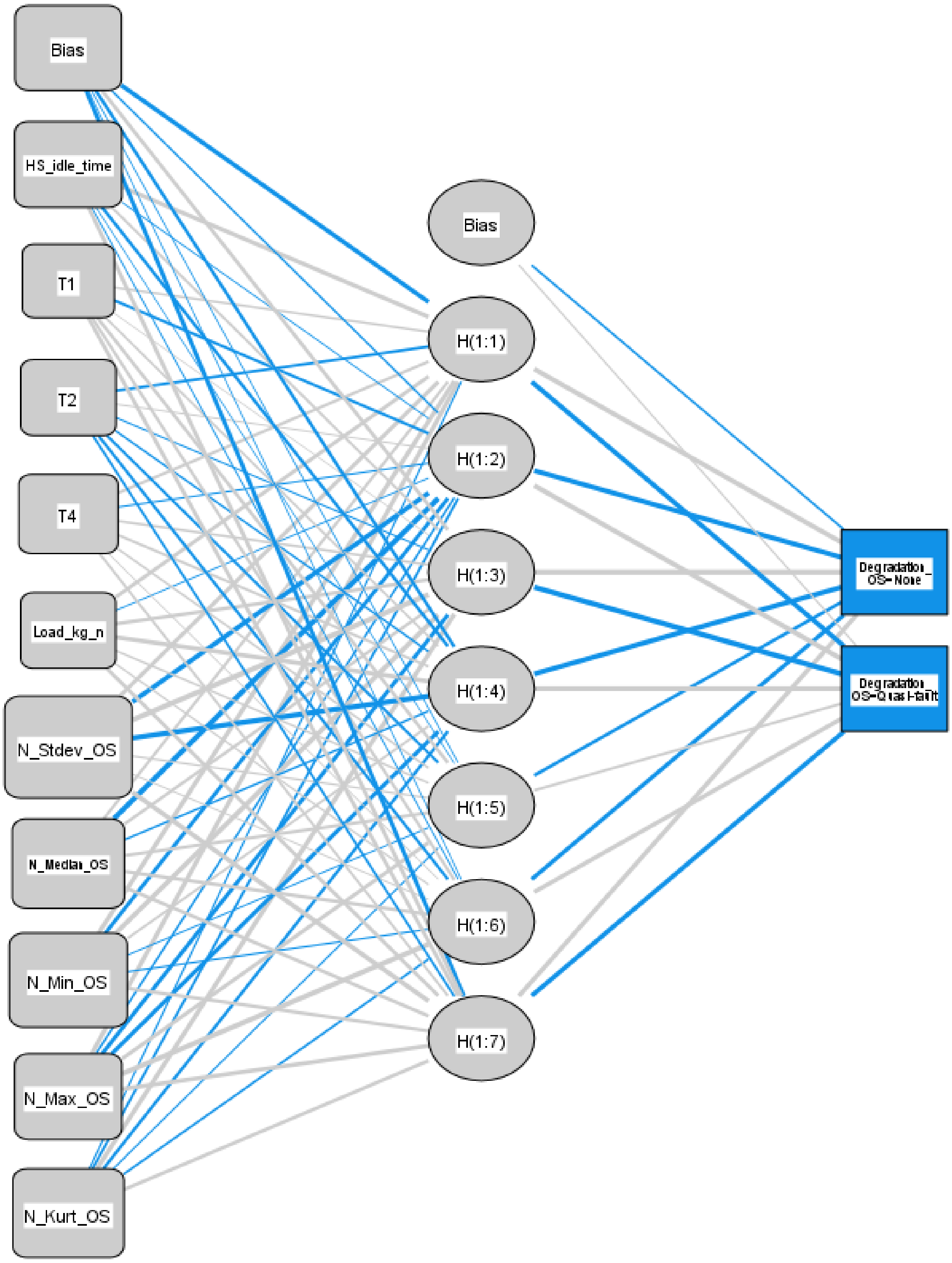


Figure 102. Multilayer perceptron artificial neural network of opening saddle with synaptic weights > 0 (blue lines) and synoptic weight < 0 (grey lines) with sigmoid activation function for hidden layer and sigmoid activation function for the output layer

The most important variable is the standard deviation in signal processing from feature extraction and prediction of binary class (none and quasi-fault) (Table 37). The standard deviation showed the highest contribution to predicting a class label, followed by minimum and median values at the opening saddle position. Therefore, the change in standard deviation can be used as an indicator for condition monitoring properties of EBM signal, alongside median and minimum that can be used for discriminant analysis of machine state.

Table 37. Independent variable importance of ANN at opening saddle position

Variable	Importance	Normalized Importance
HS_idle_time	0.104	52.3%
T1	0.032	16.1%
T2	0.047	23.5%
T4	0.066	33.0%
Load_kg_n	0.046	23.1%
N_Stdev_OS	0.199	100.0%
N_Median_OS	0.127	63.7%
N_Min_OS	0.154	77.5%
N_Max_OS	0.104	52.1%
N_Kurt_OS	0.122	61.1%

The validation of a model is done through test data. The final prediction properties show excellent prediction, i.e., classification properties of test data. The results show that 98.98% prediction is achieved from the training data, while little reduced value is given on the testing data of 94.56% (Table 38). Hence, the model for opening saddle position has shown excellent results.

Table 38. Classification results of Neural Network for opening saddle position

Sample	Observed	Predicted		
		None	Quasi-fault	Percent Correct
Training	None	355	2	99.44%
	Quasi-fault	5	324	98.48%
	Overall Percentage	52.48%	47.52%	**98.98%**
Test	None	151	8	94.97%
	Quasi-fault	8	127	94.07%
	Overall Percentage	54.08%	43.20%	**94.56%**

Although mostly in practical applications, different activation functions are used (e.g., softmax and ReLU), the computation of ANN is done in SPSS with multilayer perceptron NN, and the sigmoid function showed the best prediction properties after the trial-and-error test. However, although sigmoid showed the best prediction properties, it does necessarily not be concluded that other activation functions will not perform better in the future. In addition, different outcomes can be achieved since many different neural networks exist and different optimisation strategies are used – changes of parameters and hyperparameters. Parameters in neural networks are meant by the change of weights in an ANN, while hyperparameters include a wide range of changes before the computation of an ANN. There are a huge amount of optimisation techniques for hyperparameters. As such, a model hyperparameter is a configuration technique that is „outside“ of the model parameters – the number of hidden layers in NN and the variables that determine the learning rate of an ANN. Usually, changes in hidden layers with regularisation are done to increase accuracy by adding or removing nodes („dropout“ regularisation“), thus increasing the generalisation „power“ of a model and reducing the overfitting of a model. Although the activation function „Rectified Linear Activation Unit“ or ReLU is gaining significant attention, as an unwritten rule sigmoid function is used for making binary predictions, while softmax is used for multi-class prediction problems. Since simple ANN achieves high prediction properties, the in-depth optimisation will not be done and is beyond the scope of the thesis.

9.2.2 ARTIFICIAL NEURAL NETWORK FOR IDLE SADDLE POSITION

Monitoring the regime at idle saddle position and eliminating variables associated with sensor failure are removed since all values (readings) after non-returning the saddle in the initial position or not performing the cycle is zero. Therefore, the reduced number of training data is n = 540 (Table 39).

Table 39. Case processing summary of training data at idle saddle position

Properties		Sample	Percentage
Sample	Training	540	100.0%
Valid		540	100.0%
Excluded		0	
Total		540	

Pieces of information regarding the construction of a neural network for idle saddle position are given in Table 40. Since different positions consist of different variables, it should be noted that the change of features in different positions affects prediction properties. Ten features are extracted and used with the sigmoid activation function on hidden and output layers. The resulting neural network shows 2.013 SSE and 0.4% incorrect predictions in training (Table 41) of the model.

The number of epochs is 100. This hyperparameter explains the number of times the learning algorithm worked through an entire training set. One epoch means that each sample updated every internal model parameter through the training model. The difference between the batch and epoch in the model's training is that batch represents the number of samples processed before the model update, while epoch is the number of passes through an entire training set.

Table 40. Neural network information and parameters for idle saddle position

Layer information	Sub-layer information	Values	Features
Input Layer	Covariates	1	HS_idle_time
		2	T1
		3	T3
		4	T4
		5	Load_kg_n
		6	N_Stdev_IS
		7	N_1Q_IS
		8	N_Median_IS
		9	N_min_IS
		10	N_Kurt_IS
	Number of Units[a]		10
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		7
	Activation Function		Sigmoid
Output Layer	Dependent Variables	1	Degradation_IS
	Number of Units		2
	Activation Function		Sigmoid
	Error Function		Sum of Squares

a. Excluding the bias unit

Table 41. ANN training summary at idle saddle position

Data	Properties	Values
Training	Sum of Squares Error	2.013
	Percent Incorrect Predictions	0.4%
	Stopping Rule Used	The maximum number of epochs (100) exceeded
	Training Time	0:00:00.07

Dependent Variable: Degradation_IS

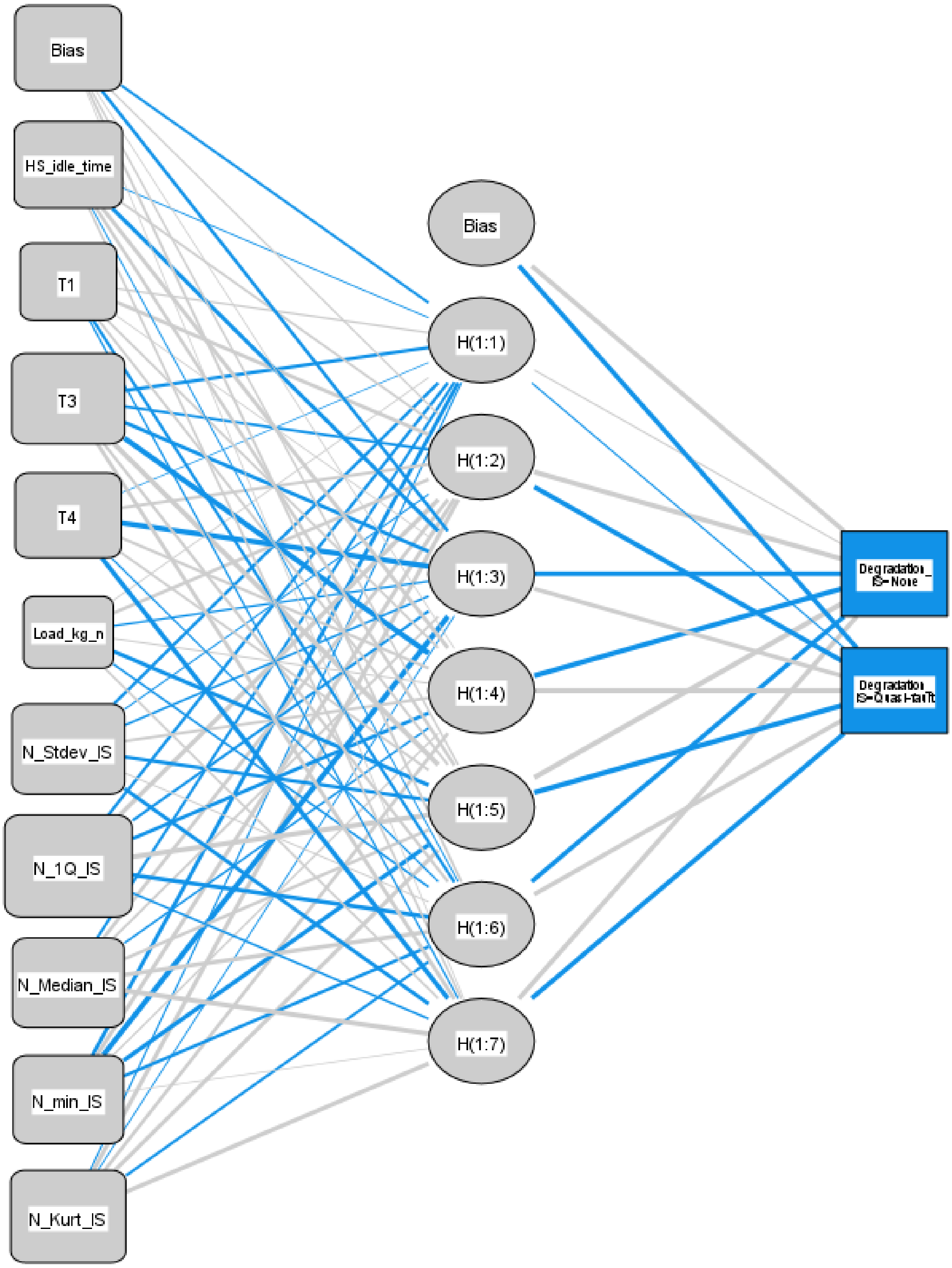


Figure 103. Multilayer perceptron artificial neural network of the idle saddle with synaptic weights > 0 (blue lines) and synoptic weight < 0 (grey lines) with sigmoid activation function for hidden layers and sigmoid activation function for the output layer

The values of associated weights of given parameters in the training model and the bias value are given in Table 42. The weights and biases are used to test the model prediction properties. The complete look of a neural network is given in Figure 103.

Table 42. Parameter estimates for ANN at idle saddle position

Predictor		Predicted								
		Hidden Layer 1							Output Layer	
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	None	Quasi-fault
Input Layer	(Bias)	-1.257	.598	-2.377	.124	.756	1.120	.122		
	HS_idle_time	-.178	.925	-3.159	3.051	2.239	-.429	.910		
	T1	.749	2.747	.138	.965	1.098	-1.789	-.718		
	T3	-2.409	-1.378	-2.728	-9.774	7.231	1.704	2.851		
	T4	-.001	1.814	-8.875	1.590	.994	-.539	-5.837		
	Load_kg_n	.157	2.408	-.754	.462	-3.158	-.769	.871		
	N_Stdev_IS	-1.879	-.461	-.824	1.584	-2.579	.435	-2.771		
	N_1Q_IS	-1.843	4.925	-1.422	-2.720	7.608	-3.643	-.819		
	N_Median_IS	-1.542	2.618	1.049	-.760	1.975	4.024	6.834		
	N_min_IS	-3.025	3.455	-8.495	.734	-4.323	-2.226	.097		
	N_Kurt_IS	-.509	4.084	-.281	2.491	3.619	-1.492	4.887		
Hidden Layer	(Bias)								6.414	-6.449
	H(1:1)								.473	-.485
	H(1:2)								7.004	-6.977
	H(1:3)								-4.648	4.611
	H(1:4)								-7.927	7.920
	H(1:5)								8.173	-8.189
	H(1:6)								-5.033	5.028
	H(1:7)								6.634	-6.652

From feature extraction and prediction of binary class (none and quasi-fault), the most important variable is the change in the first quartile range in the signal processing (Table 43). The first quartile (N_1Q_IS) shows the highest normalized importance to the model in predicting the class label, followed by kurtosis and speed of the actuator response time at idle saddle regime (T4), followed by again, the standard deviation of the signal.

Table 43. Independent variable importance of ANN at idle saddle position

Variables	Importance	Normalized Importance
HS_idle_time	0.096	54.2%
T1	0.047	26.5%
T3	0.116	65.3%
T4	0.087	49.1%
Load_kg_n	0.020	11.4%
N_Stdev_IS	0.115	64.8%
N_1Q_IS	0.177	100.0%
N_Median_IS	0.111	62.6%
N_min_IS	0.106	59.6%
N_Kurt_IS	0.126	71.2%

The change of the 1Q in the signal processing can indicate the change in the actuator's response time and the directional valve's movement. It is questionable whether the quasi-fault can be associated with the sensor response time (for opening and closing the saddle) or is affected by the degradation of the directional valve. Besides, a high association with the change of standard deviation and median values of the signal can indicate the degradation of the hydraulic power drop and needs to be further investigated for multiclass predictions. Finally, the model shows excellent prediction properties for binary values (Table 44).

Table 44. ANN classification matrix of results at idle saddle position

Sample	Observed	Predicted		
		None	Quasi-fault	Percent Correct
Training	None	354	1	99.7%
	Quasi-fault	1	184	99.5%
	Overall Percentage	65.7%	34.3%	**99.6%**
Test	None	146	2	98.6%
	Quasi-fault	2	81	97.6%
	Overall Percentage	64.1%	35.9%	**98.3%**

9.2.3 ARTIFICIAL NEURAL NETWORK FOR CLOSING SADDLE POSITION

After initial data exploration and elimination of selected features, the rest of the features at the closing saddle position have been initialized for binary prediction in the neural network. However, there were cases where the system stopped (total failure) due to sensor failure and replacement; the same samples were removed from the analysis. Therefore, unlike previous samples, 640 samples are used for training Table 45.

Table 45. Case processing summary of training data at closing saddle position

Properties		N	Percent
Sample	Training	640	100.0%
Valid		640	100.0%
Excluded		0	
Total		640	

Same as the cases with the previous two neural network training conditions, parameters from the model are represented in Table 46. All three use defined variables set before initialisation with the sigmoid activation function for hidden and output layers.

Table 46. Neural network information and parameters for closing saddle position

Layer information	Sub-layer information	Values	Properties
Input Layer	Covariates	1	T2
		2	T3
		3	T4
		4	Load_kg_n
		5	N_Stdev_CS
		6	N_Mean_CS
		7	N_RMS_CS
		8	N_1Q_CS
		9	N_IQR_CS
		10	N_Min_CS
		11	N_Skew_CS
	Number of Units[a]		11
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		8
	Activation Function		Sigmoid
Output Layer	Dependent Variables	1	Degradation_CS
	Number of Units		2
	Activation Function		Sigmoid
	Error Function		Sum of Squares

a. Excluding the bias unit

The summary of processing time and 100 epochs for training the data are represented in Table 47. However, although the stopping rule was the same, the time for training the last network took 14 sec, doubling the second training and tripling the first training network. The PC used for training is Inter(R) i3-4170 3.7GHz, 8 GB RAM, Nvidia GeForce GT 1030 graphics. After the training was done, SSE was 10.384 with 1.6% incorrect predictions with 100 epochs reached.

Table 47. ANN model summary at closing saddle opening position

Properties	Information	Values
Training	Sum of Squares Error	10.384
	Percent Incorrect Predictions	1.6%
	Stopping Rule Used	The maximum number of epochs (100) exceeded
	Training Time	0:00:00.14

Dependent Variable: Degradation_CS

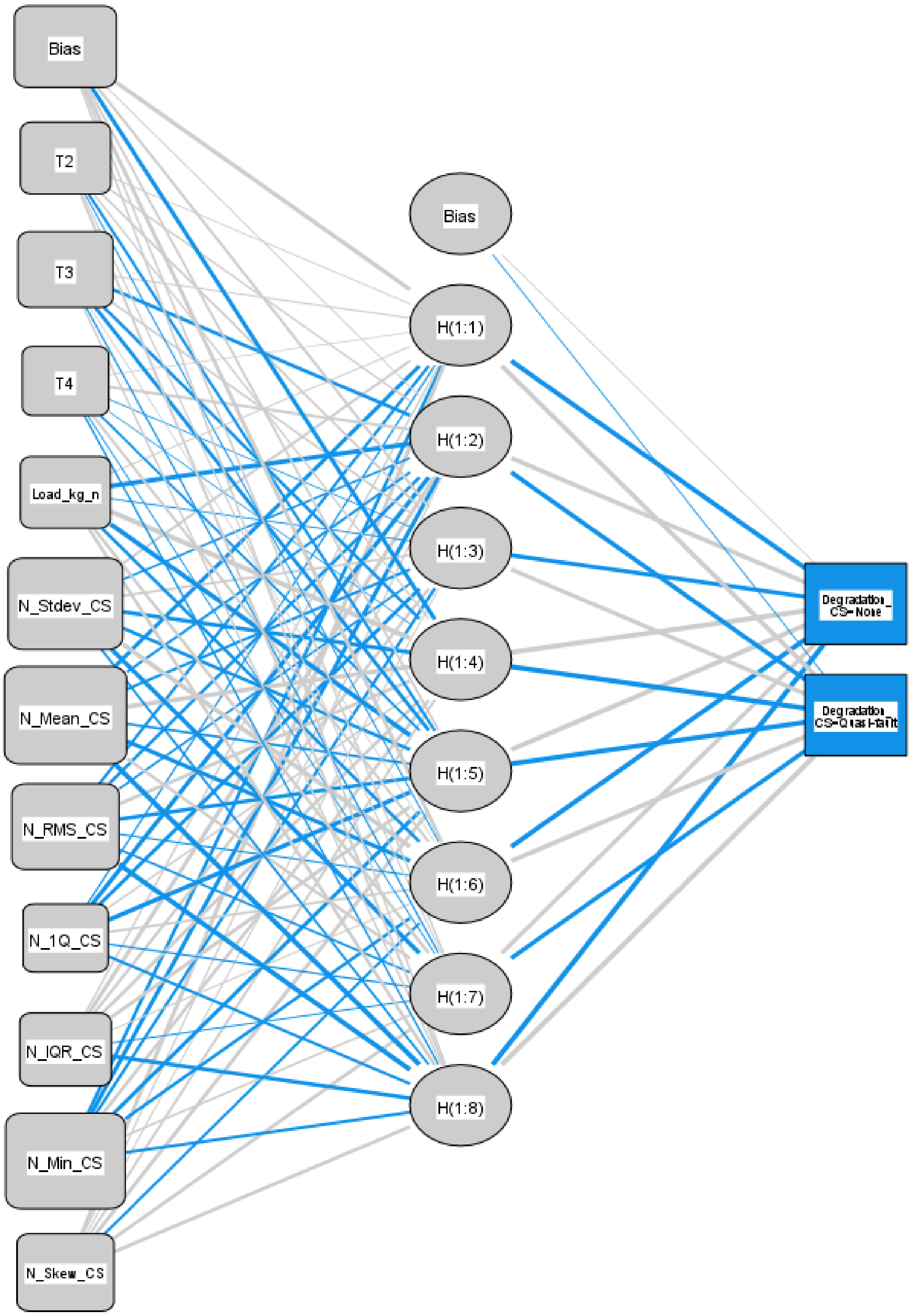


Figure 104. Multilayer perception artificial neural network of the closing saddle with synaptic weights > 0 (blue lines) and synaptic weight < 0 (grey lines) with sigmoid activation functions for hidden and output layers using features for the closing saddle regime

The values of associated weights of given parameters in the training model and the bias value are given in Table 48. The weights and biases are used to test the model prediction properties. The complete look of a neural network is given in Figure 104.

Table 48. Parameter estimates ANN at closing saddle position

Predictor		Predicted									
		Hidden Layer 1								Output Layer	
		H(1:1)	**H(1:2)**	**H(1:3)**	**H(1:4)**	**H(1:5)**	**H(1:6)**	**H(1:7)**	**H(1:8)**	**None**	**Quasi-fault**
Input Layer	(Bias)	4.199	0.175	1.436	-3.106	0.975	2.806	0.702	0.736		
	T2	0.153	0.537	0.851	0.497	-1.580	-0.224	0.414	1.245		
	T3	0.299	-2.387	0.764	-1.944	-2.538	0.081	-0.432	0.639		
	T4	0.079	1.591	-0.083	-0.020	-1.000	1.374	-0.156	-0.540		
	Load_kg_n	0.228	-5.477	-0.212	7.761	-5.605	-1.957	1.802	1.976		
	N_Stdev_CS	1.361	-0.743	1.002	-2.986	-2.157	4.978	-4.355	-0.918		
	N_Mean_CS	-2.907	-1.246	-1.521	4.622	-1.050	-3.495	1.684	-7.179		
	N_RMS_CS	-1.652	-1.925	-0.782	2.251	-2.714	-0.417	-0.814	-5.931		
	N_1Q_CS	-0.446	-4.257	-2.621	0.702	-4.686	1.116	-0.451	-1.633		
	N_IQR_CS	0.553	3.019	1.653	2.172	2.594	0.296	-0.230	-2.953		
	N_Min_CS	-2.060	-3.250	-1.673	1.976	-2.837	-1.946	0.780	-1.756		
	N_Skew_CS	2.993	0.451	0.285	1.203	2.621	-1.392	2.393	2.512		
Hidden Layer 1	(Bias)									0.119	-0.123
	H(1:1)									-5.734	5.704
	H(1:2)									4.805	-4.814
	H(1:3)									-4.234	4.216
	H(1:4)									7.780	-7.803
	H(1:5)									6.055	-6.061
	H(1:6)									-5.765	5.730
	H(1:7)									4.253	-4.270
	H(1:8)									-8.319	8.322

As presented in Table 49, the most important features for predicting are median, minimum value, and standard deviation. It is important to conclude that standard deviation marks the presence of importance for making predictions in all three cases. As it can also be observed by box and whisker plots, each sample can be improved by changing the activation function considering all of the previous variables. It can be concluded that most of the models can be attributed to factors that cause deviation in a signal, along with a change in minimum values and mean values. Hence, indeed the functional-productiveness of a system can be associated with variables for monitoring the performance of standard deviation and mean values. Finally, the overall performance of an ANN model at the closing saddle position shows somewhat reduced performance on testing data by showing a 75.3% prediction of a normal operating state.

Table 49. Independent variable importance of ANN at closing saddle position

Variables	Importance	Normalized Importance
T2	0.043	21.6%
T3	0.067	33.2%
T4	0.026	12.9%
Load_kg_n	0.043	21.3%
N_Stdev_CS	0.162	81.0%
N_Mean_CS	0.200	100.0%
N_RMS_CS	0.127	63.6%
N_1Q_CS	0.019	9.4%
N_IQR_CS	0.050	25.0%
N_Min_CS	0.186	93.1%
N_Skew_CS	0.077	38.3%

Table 50. ANN Classification matrix at closing saddle regime

Sample	Observed	None	Quasi-fault	Percent Correct
Training	None	118	10	92.2%
	Quasi-fault	0	512	100.0%
	Overall Training Percentage	18.4%	81.6%	**98.4%**
Test	None	55	18	75.3%
	Quasi-fault	4	199	98.0%
	Overall Testing Percentage	21.4%	78.6%	**92.0%**

9.3 DECISION TREE ALGORITHM FOR BINARY CLASSIFICATION

A decision tree is a non-parametric supervised learning algorithm that can be used both for prediction properties, of which prediction includes – classification and regression. Since the goal, in this case, is to distinguish between operating states, the algorithm is used for classification. In addition, the algorithm, just like naïve Bayes, can be used both for numerical and categorical classification. The algorithm consists of elements – **nodes and leaves**. The starting point of the algorithm is the **root node,** while every other node is called an **internal node**. The tree builds until it reaches a node without the need or inability to separate more. The final nodes that the algorithm reaches for making decisions are called **leaves**. The first separation is done to the internal nodes from the root node, and the algorithm keeps track of the separation. Looking at the algorithm and its classification characteristics, one may conclude that it behaves like an "IF-ELSE" algorithm, which is true because it does separation based on logical terms. However, the algorithm includes elements of **impurity** or **entropy** for selecting top nodes. The impurity determines which variable has the lowest impurity that can be used as a *"parent"* node. There are different ways to model the impurity, but the most common one used is called ***GINI*** *impurity* (I_G).

$$\begin{gathered} I_G = 1 - \sum_{j=1}^{s} p_j^2, \text{ or specifically} \\ I_G = 1 - P(y_{ab})^2 - P(y_{cd})^2 \end{gathered} \tag{9.36}$$

given that both resulted classifications (y_{ab}; y_{cd}) consist of resulting classification $y_i = \{x_a ; x_b\}$ and $y_i = \{x_c ; x_d\}$. Hence, going from the raw dataset to the decision tree, we first did the selection of the top node (root) by calculating the weighted Gini impurity score for each array of an exploratory variable. Each variable's best score of Gini impurity is then compared, and the lowest score is set as the top (root) node. Hence, for every variable the classification is done, the values are represented for each accuracy and wrong classification (Figure 106).

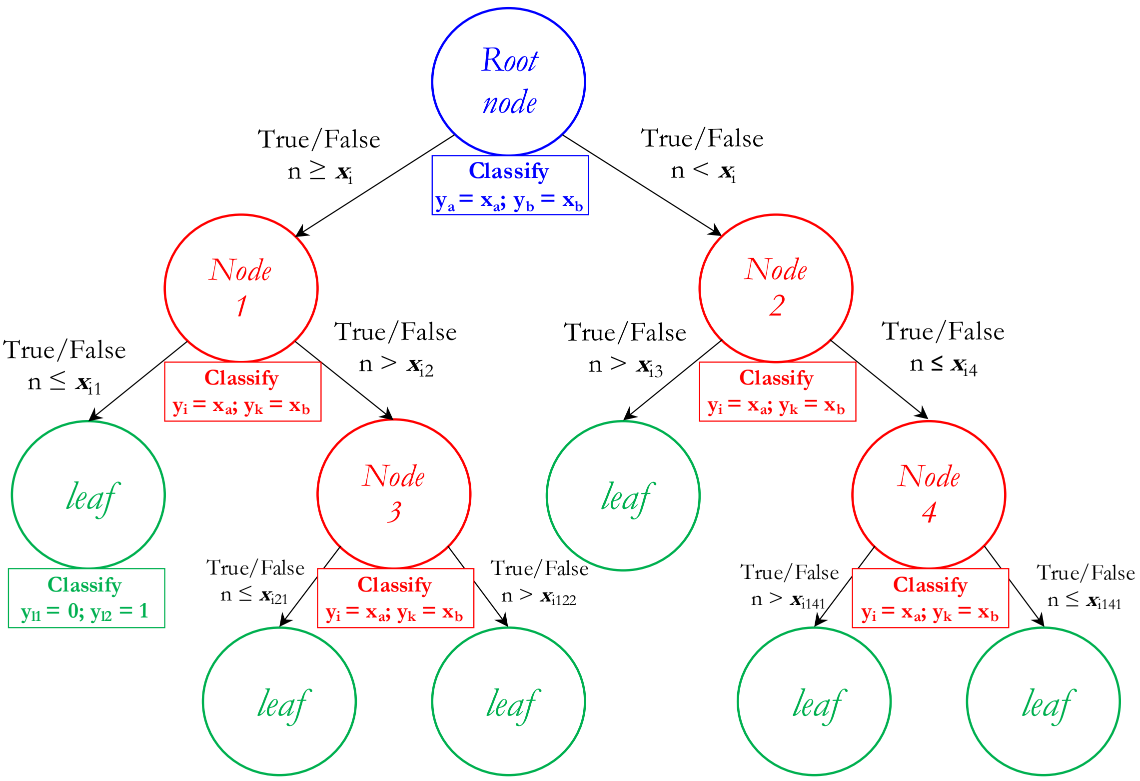


Figure 105. Graphical representation of decision tree algorithm

Calculating Gini impurity for the given variable x is done as:

$$I_{G_{x_{ab}}} = 1 - \left(\frac{a}{a+b}\right)^2 - \left(\frac{b}{a+b}\right)^2, \tag{9.37}$$

$$I_{G_{x_{cd}}} = 1 - \left(\frac{c}{c+d}\right)^2 - \left(\frac{d}{c+d}\right)^2, \tag{9.38}$$

where we get initial GINI impurity; however, since we usually do not pose the same amount of classification data N(a, b) ≠ N(c, d), then we need to calculate the weighted average:

$$Weighted\left(I_{G_{x_i}}\right) = \left(\frac{a+b}{a+b+c+d}\right) \cdot I_{G_{x_{ab}}} + \left(\frac{c+d}{a+b+c+d}\right) \cdot I_{G_{x_{cd}}}, \tag{9.39}$$

and we select the minimum weighted Gini as min$\{Weighted(GINI_{xi})_k\}$ as the root node. Following the root node, we need to calculate the weighted Gini impurity for the rest of the nodes until we use all the nodes to classify the input labels or when the node reaches the lowest score, so we do not need to separate nodes anymore. If we are considering numeric data, we first need to rank data of all variables, where after rankings, we need to calculate the Gini impurity between each point (in array) of a given sample. We then find weighted Gini impurity for every point in a given array of variable X_i and set it as the root node. The perfectly separate leaves, i.e., containing only 1 class, are called pure leaf nodes in the final *leaf nodes*. Latching on the same outcome, the resulting entropy is the lowest (*entropy* = 0), meaning that information gain, i.e., the probability of finding a precise label class, is maximum. A decision tree as a machine learning algorithm "learns" by finding an optimum solution by establishing either minimum Gini impurity or minimum entropy:

$$I_H = \sum -p_i \cdot \log(p_i) \tag{9.40}$$

where p is the probability of a given state, i = [1,0]. The model aims to find the state where it achieves maximum information gain because entropy measures information contained in a state. Let's say that we select the node as having equal probability (p(y=a)=0.5 and p(y=b)=0.5), the entropy is then 1. Since the decision tree uses gini impurity or entropy () for estimating information gain, it is usually called a **greedy** algorithm.

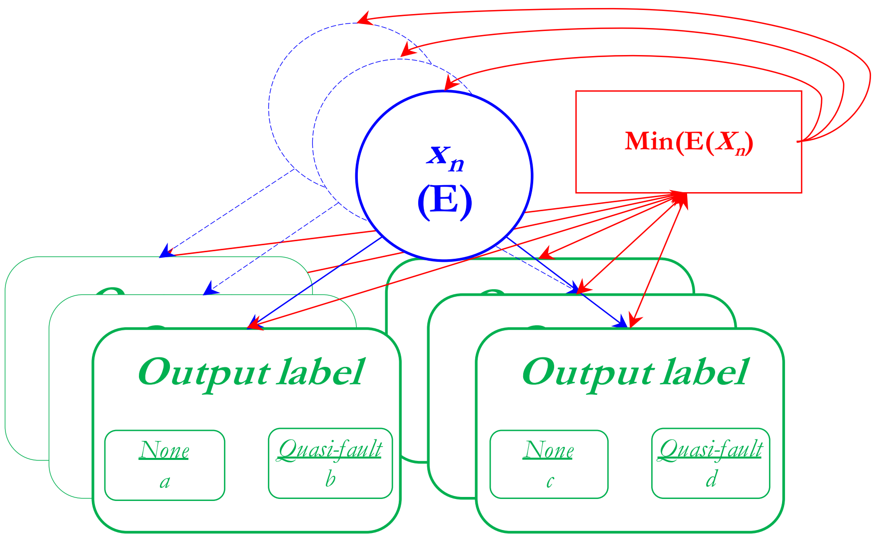


Figure 106. Selection of a node based on minimum entropy

9.3.1 DECISION CART TREE FOR OPENING SADDLE REGIME

Decision tree classification is conducted via the IBM SPSS platform. The selection of the growing method for the decision tree is CRT or usually called the CART (Classification and Regression Tree) method. Since decision trees, like almost every other ML algorithm, can be used for regression and classification, they are used for classification on all three saddle positions. Given the parameters in Table 51, the tree automatically built five trees, i.e., five nodes in the tree with 3 terminal nodes of 2 levels of depth. The two most important variables for making decisions in classifying the layers split are N_Median_OS and N_StDev_OS.

Table 51. Parameters and variables for decision tree at opening saddle position

Content	Input parameters	Variables and values
Specifications	Growing Method	CRT
	Dependent Variable	Degradation_OS
	Independent Variables	HS_idle_time, T1, T2, T4, Load_kg_n, N_Stdev_OS, N_Median_OS, N_Min_OS, N_Max_OS, N_Kurt_OS
	Validation	None
	Maximum Tree Depth	5
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables Included	N_Median_OS, N_Max_OS, N_Min_OS, N_Stdev_OS, T2, N_Kurt_OS, HS_idle_time, T1, Load_kg_n, T4
	Number of Nodes	5
	Number of Terminal Nodes	3
	Depth	2

Following that, the parent node N_Median_OS showed the highest improvement of the tree decision (node separation) due to the lowest impurity; the second level of improvement is N_StDev_OS (Table 49), which is not the case in the GNB and ANN model that selected N_Max_OS and N_Min_OS values instead of N_Median_OS, respectively. The underlying reason is that, unlike the GNB model, the DT-CART is a discriminant model and does include the parameters of Gaussian assumption as GNB does (generative); however, ANN, in this case, is also discriminative but uses mapping the outputs based on the entropy of X parameters.

Table 52. Table of surrogates of variables at opening saddle position

Parent Node	Independent Variable		Improvement	Association
0	Primary	St_N_Median_OS	0.349	
	Surrogate	St_N_Max_OS	0.129	0.533
		St_N_Min_OS	0.131	0.506
		St_N_StDev_OS	0.154	0.422
		St_T2_OS	0.041	0.292
		St_N_Kurt_OS	0.043	0.256
		Stand_HS_Idle	0.067	0.241
		St_T1_OS	0.062	0.235
		St_Load_kg_OS	0.055	0.226
		St_T4_OS	0.040	0.145
1	Primary	St_N_StDev_OS	0.052	
	Surrogate	St_N_Kurt_OS	0.016	0.586
		St_N_Min_OS	0.024	0.276
		St_T1_OS	0.017	0.276
		St_N_Median_OS	0.028	0.207
		St_Load_kg_OS	0.043	0.207
		St_N_Max_OS	0.031	0.190
		St_T2_OS	0.007	0.172
		Stand_HS_Idle	8.374E-5	0.103
		St_T4_OS	0.005	0.034

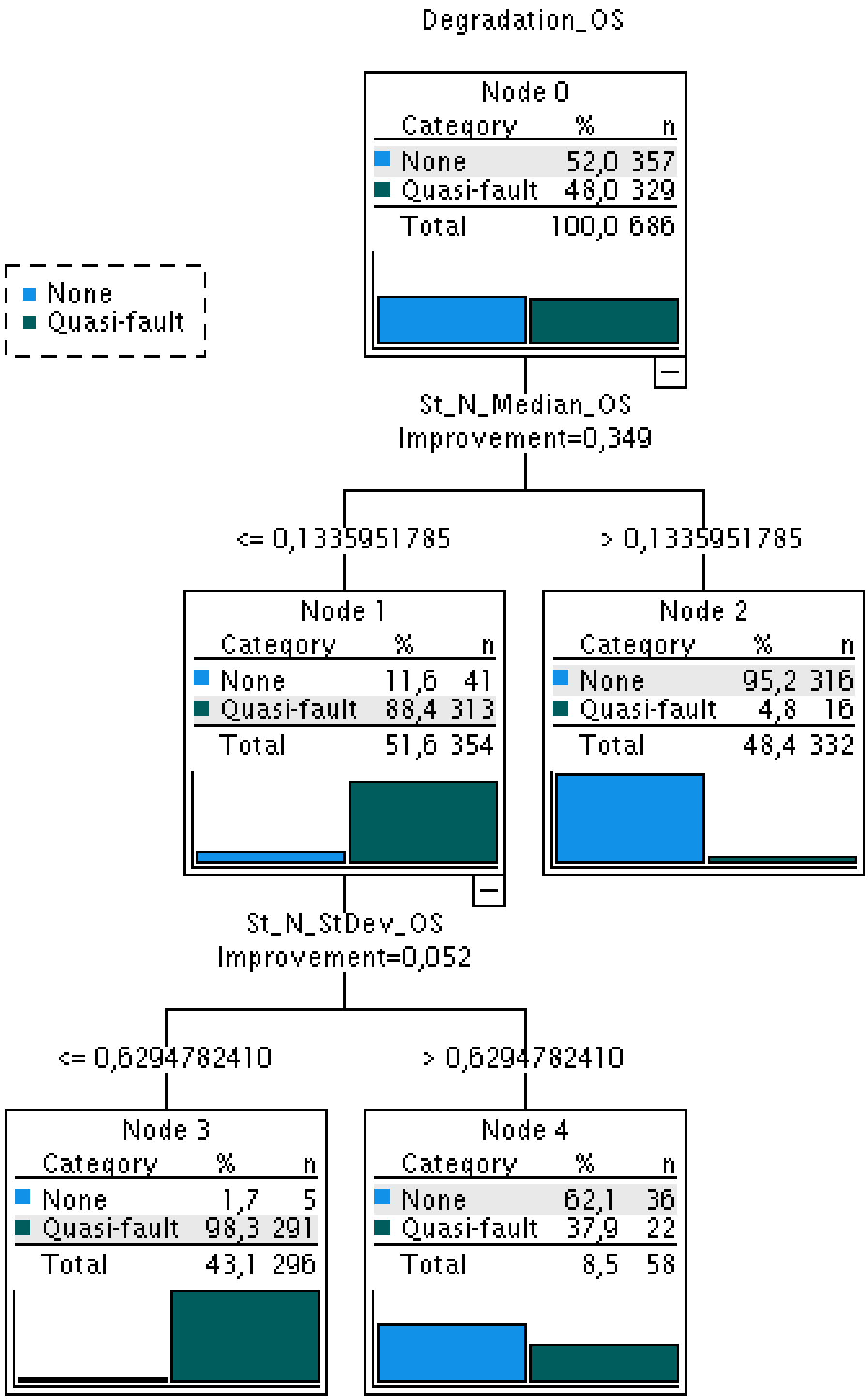


Figure 107. Decision tree of training sample at opening saddle position

Although decision trees depth can be increased to increase the model fit, however, in that case, overfitting can cause bias in getting appropriate results in achieving “optimal” classification with testing results. In order to avoid overfitting, the algorithm provides a classification tree with somewhat reasonable growth. ***Pruning*** is a method of data compression of this type of search algorithm to reduce the size of the decision tree, i.e., improving predictive accuracy by reducing overfitting. The pruning was not used in this case since the results show good predictive accuracy, and the error does not suggest an increased error of prediction accuracy.

The results of a model are shown in Table 58. The classification suggests increased bias in predicting the normal operating “None”; however, increased variance and error in prediction suggest the presence of bias, i.e., overfitting in predicting the presence of quasi-fault operating state or anomaly in prediction. The accuracy of a model shows reasonable good prediction properties; however, compared to the previous methods, a model shows a slight bias in mapping inputs to outputs given the parameters of a model in comparison to ANN. However, the model outperforms GNB since, as suggested, the model is a non-parametric algorithm, unlike GNB.

Table 53. Classification results for decision tree for opening saddle position

Sample	Observed	None	Quasi-fault	Percent Correct
Training	None	352	5	98.6%
	Quasi-fault	38	291	88.4%
	Overall Percentage	56.8%	43.1%	**93.7%**
Test	None	150	9	94.3%
	Quasi-fault	19	116	85.9%
	Overall Percentage	57.5%	39.5%	**90.5%**

Investigating the importance of variables given operating conditions and a hydraulic power system shows that for diagnostic purposes of hydraulic power deviation or detecting the presence of an anomaly in operation, it can be seen that the change can follow degradation in N_Median_OS properties (Table 54).

Table 54. Independent variable importance at opening saddle position for CART tree

Independent Variable	Importance	Normalized Importance
St_N_Median_OS	0.377	100.0%
St_N_StDev_OS	0.206	54.5%
St_N_Max_OS	0.160	42.5%
St_N_Min_OS	0.155	41.0%
St_Load_kg_OS	0.099	26.1%
St_T1_OS	0.079	20.8%
Stand_HS_Idle	0.067	17.7%
St_N_Kurt_OS	0.059	15.5%
St_T2_OS	0.048	12.6%
St_T4_OS	0.046	12.1%

The overall conclusion of degradation of the system state would be reasonably precise as a long term observation of degradation of the system since the median is robust to the presence of outliers. However, monitoring the system in close „proximity“would cause an error in a small portion of the time estimate, which is important for a timely reaction to the deviation. This includes being prepared for the deviation, removing the deviation's potential cause, and responding adequately. Hence, if we consider sequencing the operating condition of a system on, let us say, a weekly basis, it would raise significant suspicion about the validation of a model. Therefore, N_StDev_OS would be a much more adequate variable for detecting anomalies; however, further data must be collected and tested to support such suspicions.

9.3.2 DECISION CART TREE FOR IDLE SADDLE REGIME

Observing the working regime under which the system is at the idle state of operation, the system's performance in determining functionally productive and non-functionally productive is measured by various latent factors extracted from hydraulic power delivery. However, although the system provides significant information regarding the state of specific components, the most common fault that led to the system's failure and the stoppage was sensor degradation and, ultimately, failure. Therefore, since significant information provided from such a state of degradation and quite an obvious signal classification ($I_H = 0$), all the values recorded led to the total failure (xi = 0) are outliers and removed from the system. However, the rest of the factors included are represented in Table 55.

Table 55. Parameters and variables for decision tree at idle saddle position

Content	Input parameters	Variables and values
Specifications	Growing Method	CRT
	Dependent Variable	Degradation_IS
	Independent Variables	HS_idle_time, T1, T3, T4, Load_kg_n, N_Stdev_IS, N_1Q_IS, N_Median_IS, N_min_IS, N_Kurt_IS
	Validation	None
	Maximum Tree Depth	5
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables Included	N_1Q_IS, N_Median_IS, N_min_IS, N_Kurt_IS, Load_kg_n, HS_idle_time, N_Stdev_IS, T4, T1
	Number of Nodes	3
	Number of Terminal Nodes	2
	Depth	1

Observing the dependent predictors (variables) that are included in making the classification model (Table 56) shows that the most important predictor of degradation is N_1Q_IS, followed by N_Min_IS, N_Kurt_IS and N_Median_IS (Table 57). The model uses N_1Q_IS at the idle position for detecting anomalies as boundary (standardised value) between (-0.3805] and [-0.3805), in which prediction properties show around 94.4% accuracy for both labels (Table 58).

Table 56. Independent variable importance at idle saddle position for CART tree

Independent Variable	Importance	Normalized Importance
N_1Q_IS	0.328	100.0%
N_min_IS	0.163	49.6%
N_Kurt_IS	0.148	45.2%
N_Median_IS	0.133	40.5%
Load_kg	0.104	31.6%
N_Stdev_IS	0.062	18.8%
HS_idle_time_IS	0.051	15.4%
T4	0.026	7.8%
T1	0.005	1.6%

Table 57. Table of surrogates of variables at idle saddle position

Independent Variable		Improvement	Association
Primary	N_1Q_IS	0.328	
Surrogate	N_Median_IS	0.133	0.471
	N_min_IS	0.163	0.330
	N_Kurt_IS	0.148	0.325

NOTE: Threshold for improvement 0.1.

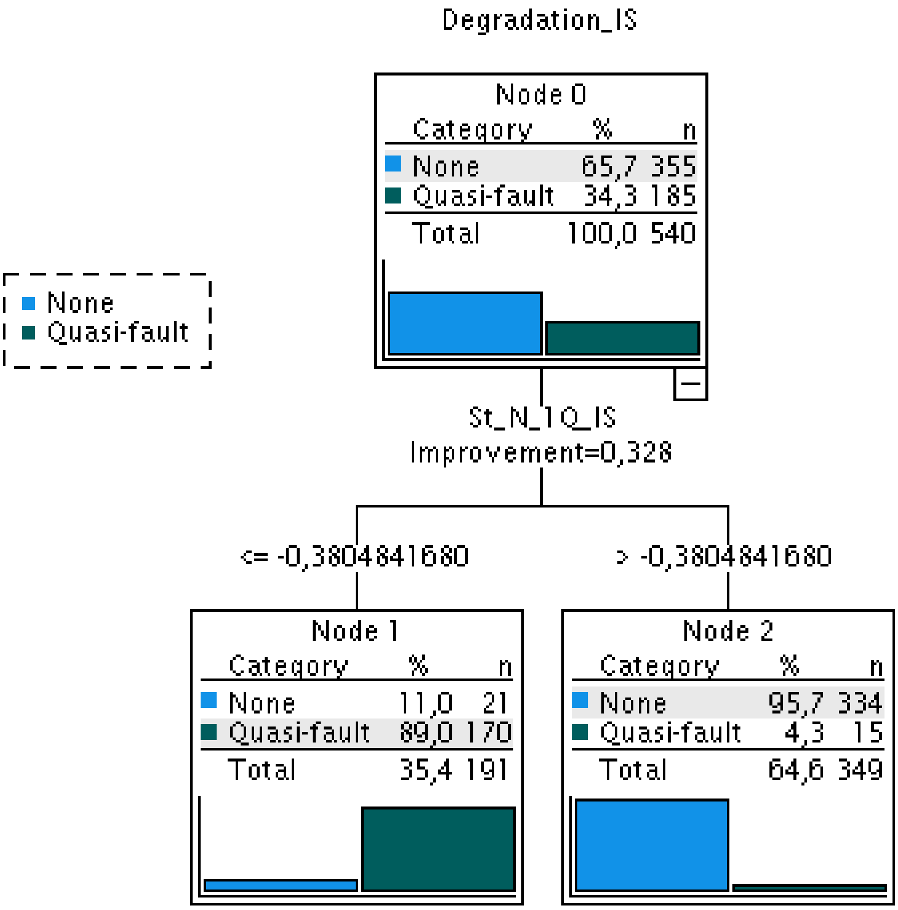


Figure 108. CART tree for idle saddle position

Although prediction accuracy for binary classification shows excellent results, the point that needs to be further analysed is the separation of labels. As mentioned, a lot of quasi-fault samples were removed from the analysis. It shows the 64%/36% data points of training and testing samples with defined labels, which suggests that this data showed better performance overall on training and testing of quasi-faults since the same accuracy is achieved with a lower amount of data. Therefore, the classification of data points is questionable since the almost double amount of data was included for training and testing samples with a normal operating state. Furthermore, it is also important to emphasise the bias and variance of the model since the functional-productiveness of a model has not been tested in real working conditions taking into account that only one variable was needed to predict with 94% accuracy.

Table 58. Decision Tree classification score for idle saddle regime

Sample	Observed	None	Quasi-fault	Percent Correct
Training	None	334	21	94.1%
	Quasi-fault	15	170	91.9%
	Overall Percentage	64.6%	35.4%	**94.38%**
Test	None	143	5	96.62%
	Quasi-fault	8	76	90.48%
	Overall Percentage	62.93%	34.05%	**94.40%**

9.3.3 DECISION CART TREE FOR CLOSING SADDLE REGIME

Finally, using all of the variables associated with the closing saddle regime, the decision tree needed to be extended to 4 terminal nodes, including three depths of decision layers and seven nodes (Figure 109). After using trial-and-error, the best performance was achieved as presented with the variables in Table 59. It is shown that N_IQR_CS is the most important variable here used for separation of degradational performance in detecting FP conditions, followed by N_RMS_CS and N_Load_CS. However, the results stress that only 14% of training data was used to build the model, whereas 86% of training data was used to build a model. It is, therefore, shown that the prediction accuracy of a model is drastically reduced in terms of a normal operating state of 60% within testing data, while over 99% accuracy was achieved in training and testing data of a model closing saddle regime. From the start of the experiment until the finish, the most common degradation was followed by sensor deviation, actuator response time in the returning position and significant degradation of cylinders in terms of speed, which can also be noticed by observing the signal itself. Therefore, much more degradation at the higher workloads. It can be observed that at a higher pressure and required flow, the degradation was extreme in certain situations, especially at the end of the experiment, which led the author to suspect that the pump was worn out—especially considering the peaks of Fe and Cr, however, without increasing over ten ppm, since filters were doing a good job of eliminating wear elements.

Table 59. Parameters and variables for decision tree at opening saddle position

Properties	Specifications	Values and explanation
Specifications	Growing Method	CRT
	Dependent Variable	Degradation_CS
	Independent Variables	T2, T3, T4, Load_kg_n, N_Stdev_CS, N_Mean_CS, N_RMS_CS, N_1Q_CS, N_IQR_CS, N_Min_CS, N_Skew_CS
	Validation	None
	Maximum Tree Depth	5
	Minimum Cases in Parent Node	100
	Minimum Cases in Child Node	50
Results	Independent Variables Included	N_IQR_CS, N_1Q_CS, N_Min_CS, N_Stdev_CS, N_Mean_CS, N_Skew_CS, T3, Load_kg_n, T4, T2, N_RMS_CS
	Number of Nodes	7
	Number of Terminal Nodes	4
	Depth	3

Moreover, it should also be emphasised that without the support of elemental analysis, which was conducted properly, however, WDXRF results showed no significant deviations of Fe and Cr and are unable to be used validity since the resolution of detection need to be higher than 10 ppm in order for the results to be valid, due to the sensitivity of XRF spectrophotometry.

Table 60. Classification matrix score for decision tree at closing saddle position

Sample	Observed	Predicted		
		None	Quasi-fault	Percent Correct
Training	None	89	39	69.53%
	Quasi-fault	2	519	99.62%
	Overall Percentage	14.02%	86.0%	**93.68%**
Test	None	44	29	60.27%
	Quasi-fault	1	201	99.51%
	Overall Percentage	16.67%	72.83%	**89.13%**

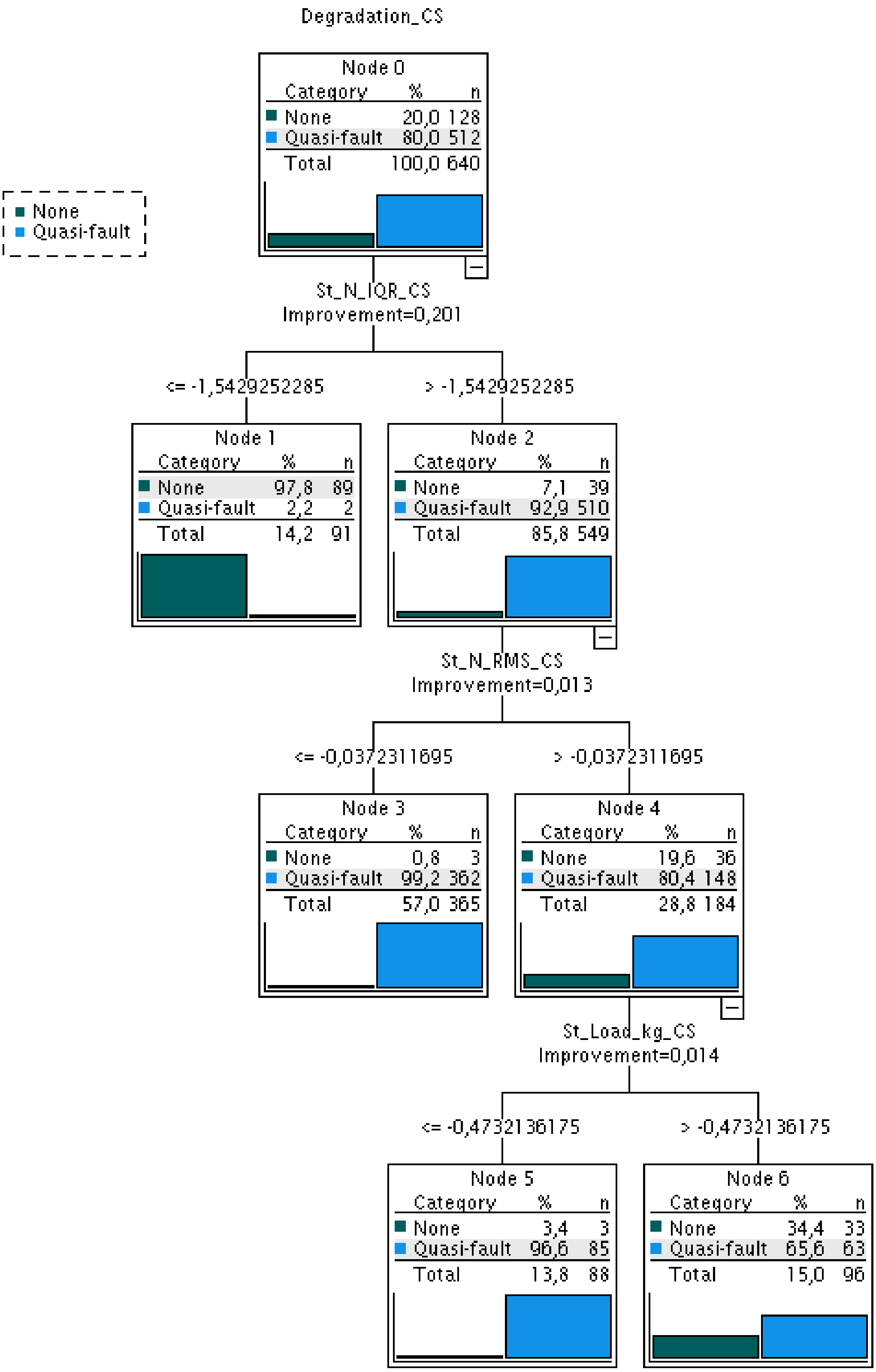


Figure 109. CART Tree for closing saddle position

9.4 LOGISTIC REGRESSION

A logistic regression model or *logistic unit* (**logit**) model is a probability model that models input parameters (x_i) and provides an output probability value modified according label value (y : R = {1, 2,… k}). Modifying it is meant that with given inputs, the model provides a probability value f(x) = {0, 1}, where class labels are set based on the probability boundaries. The thesis provides the usage of binary classification using the logit function. In a binary logistic regression model, the dependent variable y is categorical, defined as None and Quasi-fault. Input predictors or independent variables can be used both as binary variables or continuous variables, where the corresponding probability can be any value between 0 and 1, which are set for the operating state depending on the threshold as {None = 0; Quasi-fault = 1}.

Mathematically speaking, the logit function is given as:

$$logit(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x \ldots \beta_i x + \varepsilon, \tag{9.41}$$

where the probability of x is given as:

$$p(x) = \frac{1}{1+e^{-\frac{x-\varsigma}{\xi}}}, \tag{9.42}$$

where ς is the location parameter (cutoff point of the curve), and ξ is the scale parameter. Setting the equation with intercept and coefficient according to known regression notation using β:

$$p(x) = \frac{1}{1+e^{-(\beta_0+\beta_1 \cdot x)}}, \tag{9.43}$$

where $\beta_0 = -\varsigma/\xi$, known as intercept and $\beta_1 = 1/\xi$ is the coefficient for given variable x. Hence, to solve logistic regression, we need to eliminate the natural logarithm in eq (9.43) as:

$$\frac{p}{1-p} = e^{\beta_0+\beta_1 x}, \tag{9.44}$$

using simple algebra:

$$\mathrm{p} = e^{\beta_0+\beta_1 x}\,(1-p), \tag{9.45}$$

distributing:

$$\mathrm{p} = e^{\beta_0+\beta_1 x} - e^{\beta_0+\beta_1 x} \cdot p, \tag{9.46}$$

moving to the left-hand side:

$$\mathrm{p} + e^{\beta_0+\beta_1 x} \cdot p = e^{\beta_0+\beta_1 x}, \tag{9.47}$$

factoring the equation, we get:

$$\mathrm{p}(1 + e^{\beta_0+\beta_1 x}) = e^{\beta_0+\beta_1 x}, \tag{9.48}$$

to get the final probability estimation as:

$$\mathrm{p} = \frac{e^{\beta_0+\beta_1 x}}{1 + e^{\beta_0+\beta_1 x}}. \tag{9.49}$$

9.4.1 LOGISTIC REGRESSION FOR OPENING SADDLE POSITION

A logistic regression model was created, and coefficients (β_i) with constant (β_0) are given in Table 61. The influence and significance of each variable can be concluded based on the Wald test. The Wald test suggests whether the exploratory variable in a model (predictor) affects or adds value to the model. It can be said that the parameters with low values ~ zero can be deleted without much effect on the model. The model is represented as given in Table 61.

Table 61. Variables in the equation of LR for opening saddle position

Properties		B	S.E.	Wald	df	Sig.	Exp(B)	95% Lower	95% Upper
Step 1[a]	HS_idle_time	-0.305	0.167	3.339	1	0.068	0.737	0.531	1.022
	T1	0.290	0.285	1.034	1	0.309	1.336	0.764	2.337
	T2	1.334	0.359	13.791	1	<0.001	3.796	1.878	7.675
	T4	-1.085	0.339	10.225	1	0.001	0.338	0.174	0.657
	Load_kg_n	-1.640	0.306	28.813	1	<0.001	0.194	0.107	0.353
	N_Stdev_OS	-14.079	1.700	68.552	1	<0.001	0.000	0.000	0.000
	N_Median_OS	-2.177	0.388	31.495	1	<0.001	0.113	0.053	0.243
	N_Min_OS	-9.703	1.184	67.152	1	<0.001	0.000	0.000	0.001
	N_Max_OS	-0.276	0.268	1.062	1	0.303	0.759	0.449	1.283
	N_Kurt_OS	-6.312	0.757	69.460	1	<0.001	0.002	0.000	0.008
	Constant	-0.148	0.260	0.323	1	0.570	0.863		

a. Variable(s) entered on step 1: HS_idle_time, T1, T2, T4, Load_kg_n, N_Stdev_OS, N_Median_OS, N_Min_OS, N_Max_OS, N_Kurt_OS.

Although the model shows the highest accuracy considering the threshold of 0.52 (Table 62) for classification, the overall resulted function with testing data shows a discrepancy with the prediction accuracy of normal operating conditions.

Table 62. Logistic regression formulation and parameters at opening saddle position

Properties	Model parameters and values
Model equation	logit(P) = log(P / (1 - P)) = -0.148 - 2.177 N_Median_OS - 14.079 N_StDev_OS - 9.703 N_Min_OS - 0.276 N_Max_OS + 0.29 T1 - 0.305 HS_Idle + 1.334 T2- 1.085 T4 - 1.64 Load_kg - 6.312 N_Kurt_OS
Best threshold (cutoff)	0.52
Original label None/Quasi-fault	Logistic regression label: 0/1

The ROC characteristics show good prediction properties of a model, where AUC shows a threshold of 99.2% with training data, with 98.7% with 10-fold-cross-validation (Table 63). However, observing a model under test conditions shows that the overall accuracy of a model is only 86.8% (Table 64); even though the model shows good prediction properties in training (Figure 110), however, the results are questionable in terms of practical (test) validity (Figure 111).

Table 63. Performance of a model at opening saddle position

Property	AUC	Sensitivity	Specificity
Training/Discovery	0.993 (0.992 ~ 0.994)	0.957 (0.950 ~ 0.965)	0.965 (0.959 ~ 0.971)
10-fold Cross-Validation	0.987 (0.979 ~ 0.995)	0.954 (0.954 ~ 0.977)	0.955 (0.934 ~ 0.977)

Table 64. Classification matrix for logistic regression at opening saddle position

Sample	Observed	None	Quasi-fault	Percent Correct
Training	None	338	12	96.6%
	Quasi-fault	19	317	94.3%
	Overall Percentage	52.0%	48.0%	**95.5%**
Test	None	133	12	91.7%
	Quasi-fault	27	124	82.1%
	Overall Percentage	54.1%	45.9%	**86.8%**

a. cutoff value at 0.4

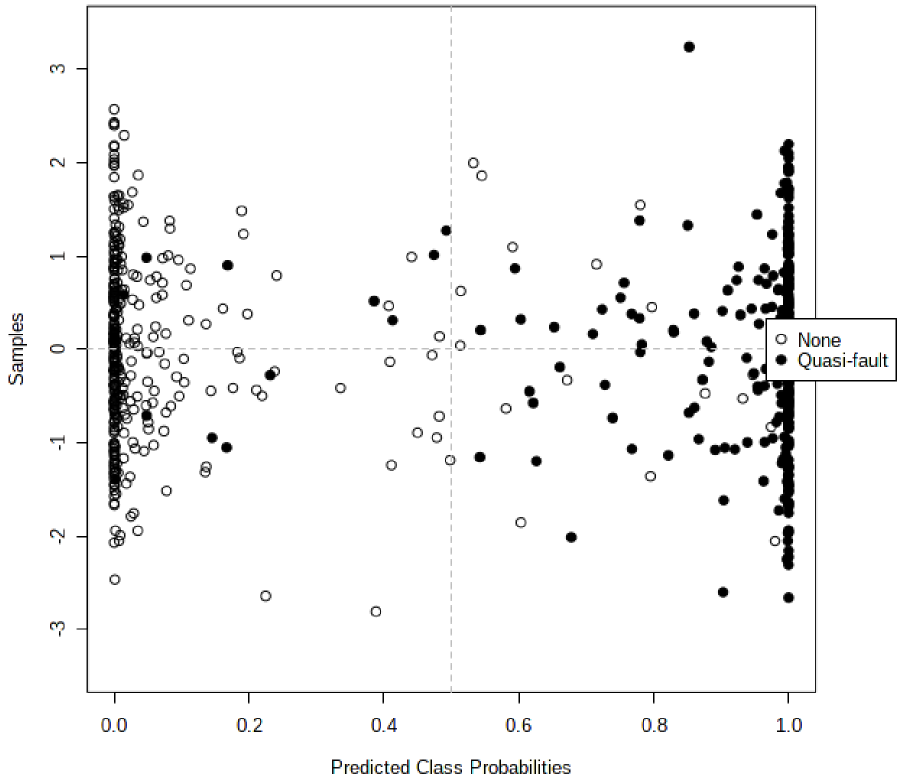


Figure 110. Logistic regression training data classification at opening saddle position

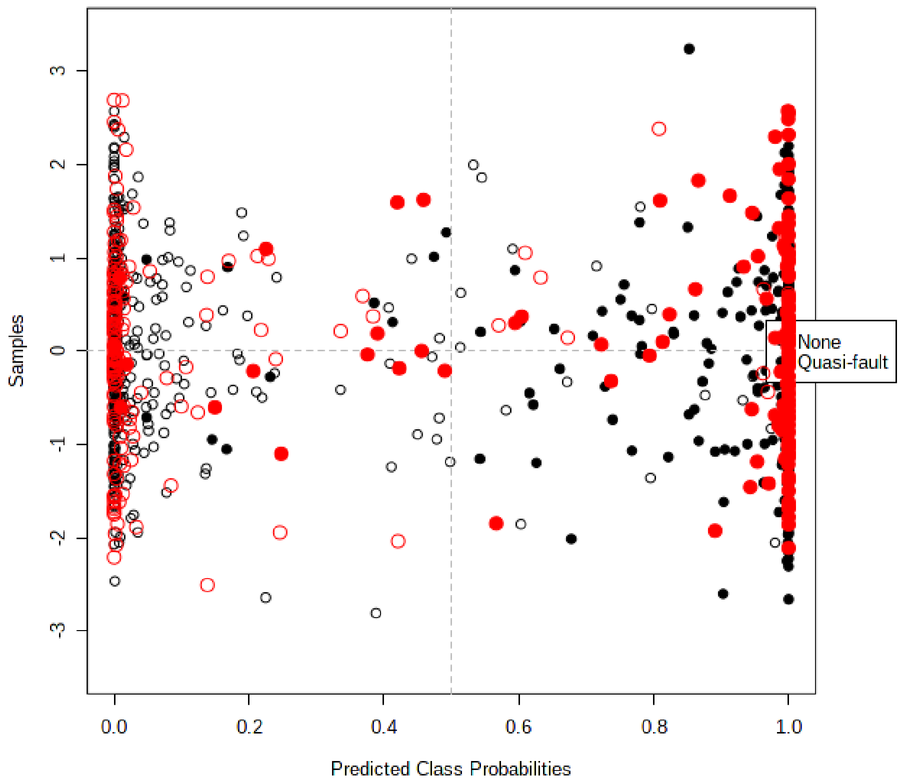


Figure 111. Logistic regression testing data classification at idle saddle position

9.4.2 LOGISTIC REGRESSION FOR IDLE SADDLE POSITION

The following variables are established for LR classification (Table 65). Although variables like HS_Idle_time; T1; Load_kg_n; N_Median_IS; N_min_IS; can be excluded from the equation (Table 66), they do not affect the final results given the state of the idle position; they are preserved for the sake of comparison between the models. Furthermore, observing the variable importance for LR idle saddle, the results suggest the most important variables are N_1Q_IS, N_StDev_IS and T3. It is reasonable that time for returning to the initial state T3 has an impact; the discrepancy of hydraulic power (effect of flow deviation) can be associated with 1Q and StDev degradation, thus measuring the flow change deviation.

Table 65. Variables in the equation for idle saddle position

Properties		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	HS_idle_time	-1.172	1.117	1.102	1	0.294	0.310
	T1	-0.184	0.331	0.310	1	0.577	0.832
	T3	-2.621	0.788	11.055	1	<0.001	0.073
	T4	-0.606	0.489	1.533	1	0.216	0.546
	Load_kg_n	-0.009	0.326	0.001	1	0.979	0.991
	N_Stdev_IS	1.666	0.382	18.994	1	<0.001	5.289
	N_1Q_IS	-5.936	0.980	36.689	1	<0.001	0.003
	N_Median_IS	0.028	0.464	0.004	1	0.952	1.028
	N_min_IS	-0.145	0.244	0.351	1	0.553	0.865
	N_Kurt_IS	-1.121	0.409	7.520	1	0.006	0.326
	Constant	-3.883	0.728	28.477	1	<0.001	0.021

a. Variable(s) entered on step 1: HS_idle_time, T1, T3, T4, Load_kg_n, N_Stdev_IS, N_1Q_IS, N_Median_IS, N_min_IS, N_Kurt_IS.

Table 66. Logistic regression formulation and parameters at idle saddle position

Properties	Model parameters and values
Model equation	logit(P) = log(P / (1 - P)) = -3.883 - 5.936 N_1Q_IS + 0.028 N_Median_IS - 1.121 N_Kurt_IS - 0.145 N_min_IS + 1.666 N_Stdev_IS - 1.172 HS_idle_time_IS - 0.009 Load_kg - 0.606 T4 - 0.184 T1 - 2.621 T3
Best threshold (cutoff)	0.41
Original label None/Quasi-fault	Logistic regression label: 0/1

The final classification results show that, unlike GNB and Decision CART tree, they show high accuracy on training (Figure 112) and testing data (Figure 113), although little underscored in comparison to ANN (Table 67). It can be concluded that degradation resembles a somewhat exponential (or Weibull) degradational pattern since data behaves as non-parametric and non-linear classification; therefore, it needs to be used. The final performance of a model shows around 96% accuracy with 10-fold-cross validation (Table 68).

Table 67. LR Classification matrix for idle saddle position

Sample	Observed	None	Quasi-fault	Percent Correct
Training	None	345	10	97.2%
	Quasi-fault	7	178	96.2%
	Overall Percentage	65.2%	34.8%	**96.9%**
Test	None	146	2	98.6%
	Quasi-fault	6	78	92.9%
	Overall Percentage	64.2%	34.5%	**96.6%**

a. cutoff value at 0.5

Table 68. Performance of a model at idle saddle position

Property	AUC	Sensitivity	Specificity
Training/Discovery	0.995 (0.994 ~ 0.996)	0.980 (0.973 ~ 0.987)	0.966 (0.960 ~ 0.972)
10-fold Cross-Validation	0.990 (0.983 ~ 0.997)	0.968 (0.968 ~ 0.993)	0.949 (0.926 ~ 0.972)

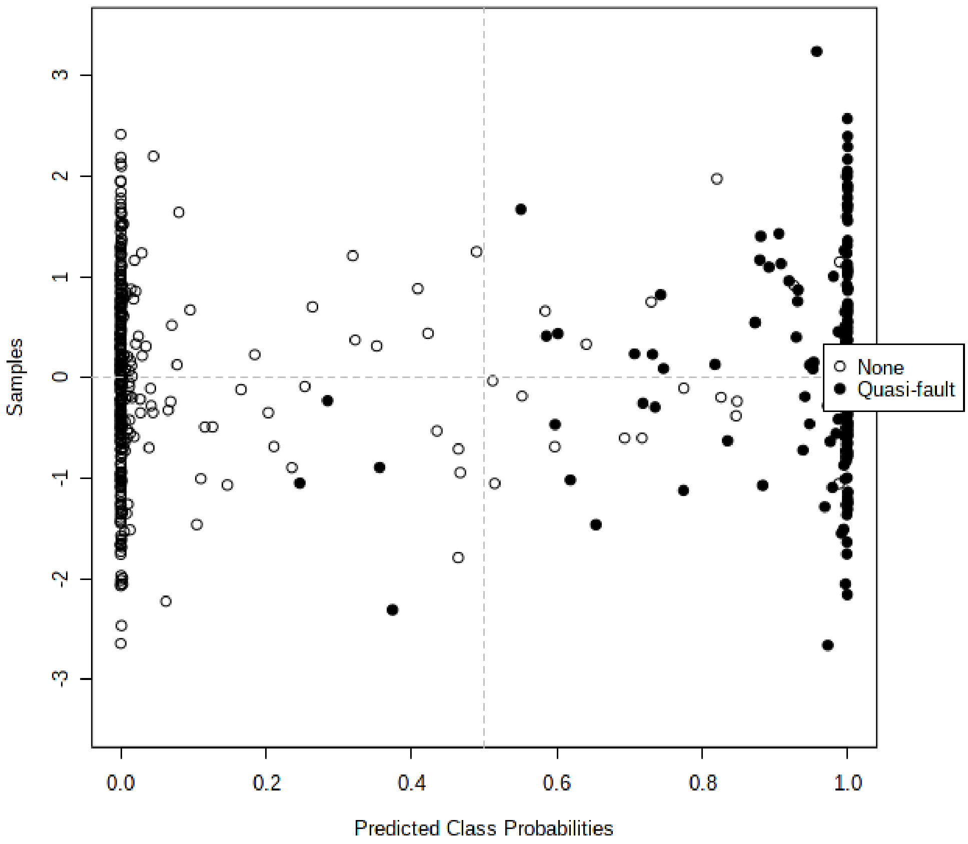


Figure 112. Logistic regression training classification at idle saddle position

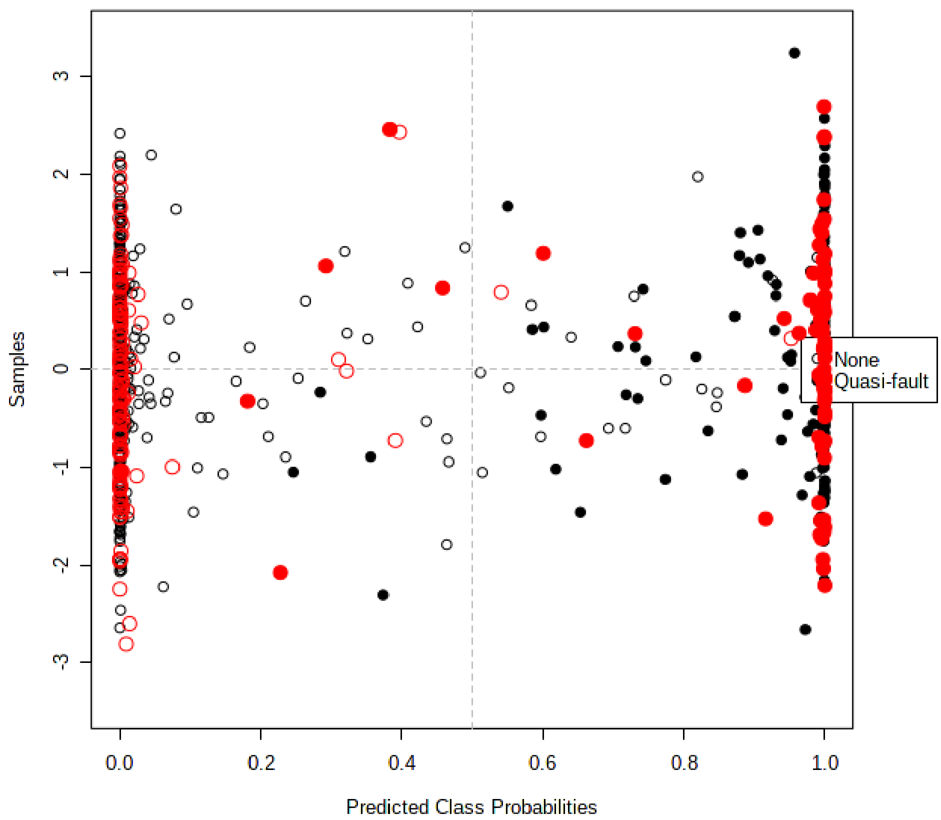


Figure 113. Logistic regression classification score of testing data at closing saddle position

9.4.3 LOGISTIC REGRESSION FOR CLOSING SADDLE POSITION

Reviewing the results from the LR model at the closing saddle position, the following equation shows that only N_IQR_CS; Constant (intercept) and Load_kg_n could be used to set the classification model (Table 69), while the rest of the variables (predictors) could not be considering that they are contributing to the model improvement (Table 70).

Table 69. LR Summary of features and associted weights at closing saddle position

Properties		B	S.E.	Wald	df	Sig.	Exp(B)	95% Lower	95% Upper
Step 1[a]	T2	0.453	0.203	4.961	1	0.026	1.573	1.056	2.343
	T3	0.404	0.350	1.333	1	0.248	1.498	0.754	2.974
	T4	0.011	0.195	0.003	1	0.955	1.011	0.690	1.480
	Load_kg_n	-0.656	0.217	9.128	1	0.003	0.519	0.339	0.794
	N_Stdev_CS	5.490	2.905	3.572	1	0.059	242.168	0.816	71865.246
	N_Mean_CS	0.698	4.221	0.027	1	0.869	2.009	0.001	7865.099
	N_RMS_CS	-5.511	5.523	0.996	1	0.318	0.004	0.000	203.207
	N_1Q_CS	-1.908	1.330	2.058	1	0.151	0.148	0.011	2.011
	N_IQR_CS	-2.629	1.024	6.598	1	0.010	0.072	0.010	0.536
	N_Min_CS	-0.833	1.700	0.240	1	0.624	0.435	0.016	12.183
	N_Skew_CS	-0.152	0.293	0.270	1	0.603	0.859	0.483	1.526
	Constant	2.714	0.570	22.662	1	<0.001	15.090		

a. Variable(s) entered on step 1: T2, T3, T4, Load_kg_n, N_Stdev_CS, N_Mean_CS, N_RMS_CS, N_1Q_CS, N_IQR_CS, N_Min_CS, N_Skew_CS.

Table 70. Logistic regression formulation and parameters at idle saddle position

Properties	Model parameters and values
Model equation	logit(P) = log(P / (1 - P)) = 2.714 + 0.698 N_Mean_CS - 1.908 N_1Q_CS - 0.833 N_Min_CS - 5.511 N_RMS_CS - 2.629 N_IQR_CS + 5.49 N_Stdev_CS + 0.453 T2 - 0.656 Load_kg + 0.011 T4 + 0.404 T3 - 0.152 N_Skew_CS
Best threshold (cutoff)	0.84
Original label None/Quasi-fault	Logistic regression label: 0/1

Although the model shows excellent prediction properties concerning the classification of quasi-fault label points, the model shows poor prediction properties concerning normal operating conditions (Table 71). Besides, as emphasised before, a small sample of training and testing data shows a high discrepancy between training (Figure 114) and testing samples of „None“ labels (Figure 115) since many anomalies have been detected during the recording of the experiment. It should be emphasised that even though the model possesses high sensitivity and specificity score of 87% (Table 72), the model does not possess high accuracy of None data points, especially during the testing period of the LR model.

Table 71. LR Classification matrix score at closing saddle position

Sample	Observed	None	Quasi-fault	Percent Correct
Training	None	92	36	71.9%
	Quasi-fault	7	505	98.6%
	Overall Training Percentage	15.5%	84.5%	**93.3%**
Test	None	43	30	58.9%
	Quasi-fault	0	203	98.5%
	Overall Testing Percentage	17.8%	72.2%	**89.1%**

a. cutoff value at 0.8

Table 72. Performance of a model at closing saddle position

Property	AUC	Sensitivity	Specificity
Training/Discovery	0.963 (0.958 ~ 0.968)	0.873 (0.863 ~ 0.882)	0.899 (0.882 ~ 0.917)
10-fold Cross-Validation	0.950 (0.928 ~ 0.972)	0.873 (0.873 ~ 0.902)	0.883 (0.827 ~ 0.939)

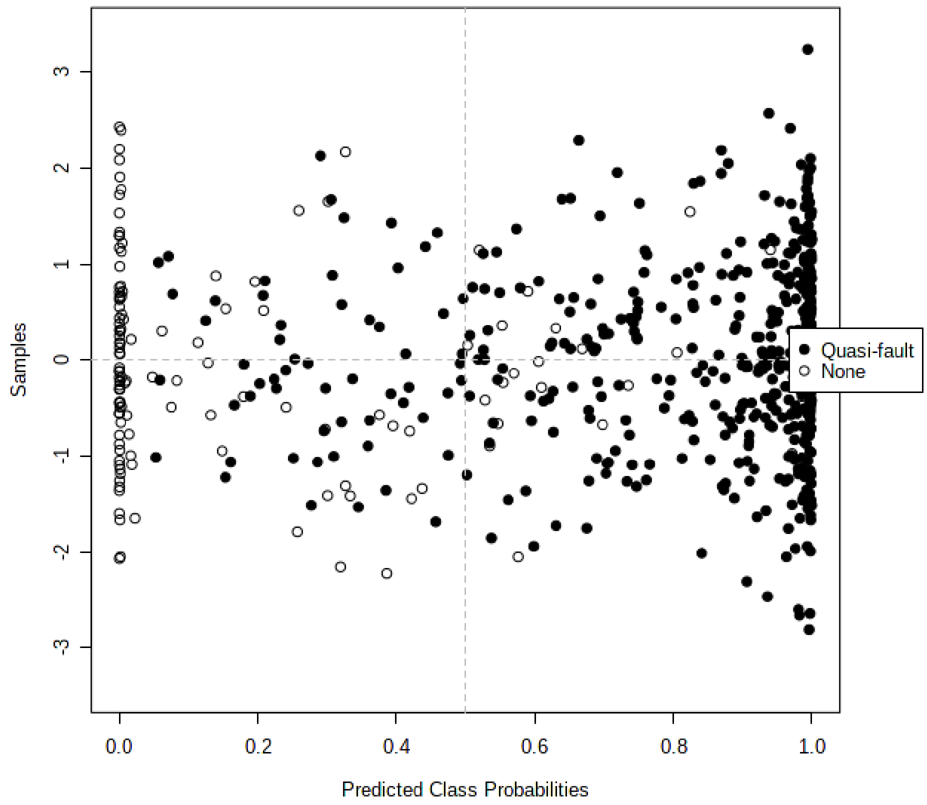


Figure 114. Logistic regression classification score of training data at closing saddle position

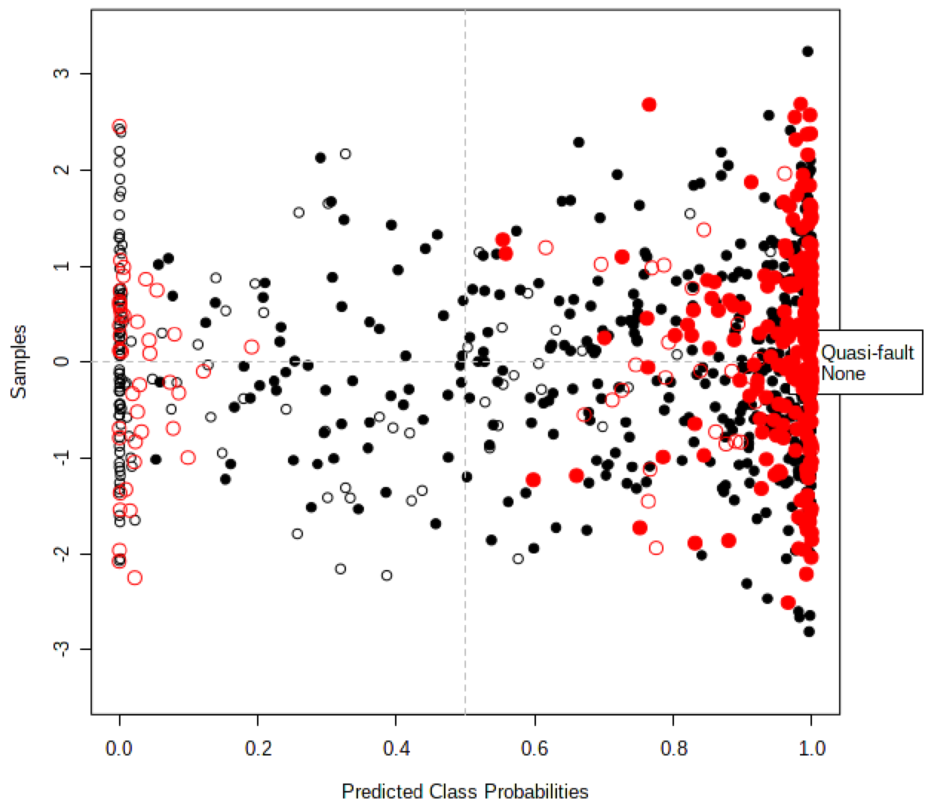


Figure 115. Logistic regression classification score of testing data at closing saddle position

9.5 kNN CLASSIFICATION ALGORITHM

The *k*NN stands for *k* Nearest Neighboor machine learning algorithm. It is one of the simplest non-parametric supervised machine learning algorithms ([134]) that is usually applied for clustering (classification), however, it can be used both for classfication and regression (and imputation). The algorithm works on a principle of storing cases based on the *k* or number of nearest points to classify new points based on the similarity between given meaure (Figure 116).

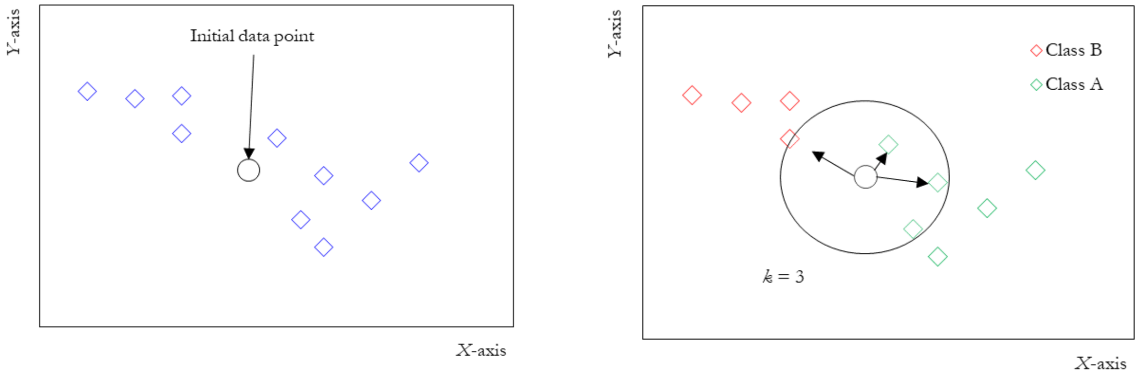


Figure 116. Graphical intepretation of *k*NN initialisation (left) and *k* = 3 (right) classification

Therefore, the parameter k explains how many data points near the specific number should be included in the majority voting process. There is no ultimate formula for choosing the *k* parameter; however, a general rule is to select *k* based on the square root. Sometimes using an error plot of accuracy plot can determine the appropriate parameter of *k*. Therefore, the first step is choosing the right *k* value corresponding to several factors: application settings, dataset size, dimensionality and classification problem. Usually, concerning binary classification, the *k*NN uses odd numbers. Secondly, the distance function (distance between data points) is calculated based on Euclidian (d_E), Minkowski (d_M) or Manhattan distance (d_{MH}). Usually, this *k*NN metric for finding distance metrics is called hyperparameters. The general form of distance between given *a* and *b* points as:

$$d(x_a, x_b) = \left(\sum_{j=1}^{p} \left(x_{aj} - x_{bj}\right)^q\right)^{\frac{1}{q}}, \tag{9.50}$$

where the value of *p* equals the number of features and *q* is a constant (1 or 2). This general form can be usually described as Minkowski distance and can be seen in the literature in the form of:

$$d_M(x_a, x_b) = \sqrt[q]{|x_{a1} - x_{b1}|^q + |x_{a2} - x_{b2}|^q + \cdots + \left|x_{ap} - x_{bp}\right|^q}, \tag{9.51}$$

where in the case of $q = 2$ the calculation is then represented as *Euclidian* distance:

$$d_E(x_a, x_b) = \sqrt[2]{|x_{a1} - x_{b1}|^2 + |x_{a2} - x_{b2}|^2 + \cdots + \left|x_{ap} - x_{bp}\right|^2}, \tag{9.52}$$

and in the case of $q = 1$, the calculation is then represented as a simple *Manhattan* distance:

$$d_{MH}(x_a, x_b) = \sqrt{|x_{a1} - x_{b1}| + |x_{a2} - x_{b2}| + \cdots + |x_{an} - x_{bn}|}. \tag{9.53}$$

The classification using kNN is done in the following subsections using IBM SPSS software.

9.5.1 K-NN CLASSIFICATION ALGORITHM FOR OPENING SADDLE POSITION

The graphs and classification matrix results do not provide too much explanatory information regarding the classification methodology. The results show the classification results represented by reduced projection of higher dimensions and the results of assigning classes to specific binary classes. As was the case with previous ML algorithms, the best separation of the opening saddle includes N_StDev_OS, N_Median_OS, N_Min_OS, and N_Max_OS; the same are used to visualise the separation of the kNN algorithm and are given in Figure 117. The classification results (Table 71) show up to 91% overall accuracy, with lower accuracy in determining normal operating conditions. Unlike previous algorithms, the classification results show slightly reduced accuracy.

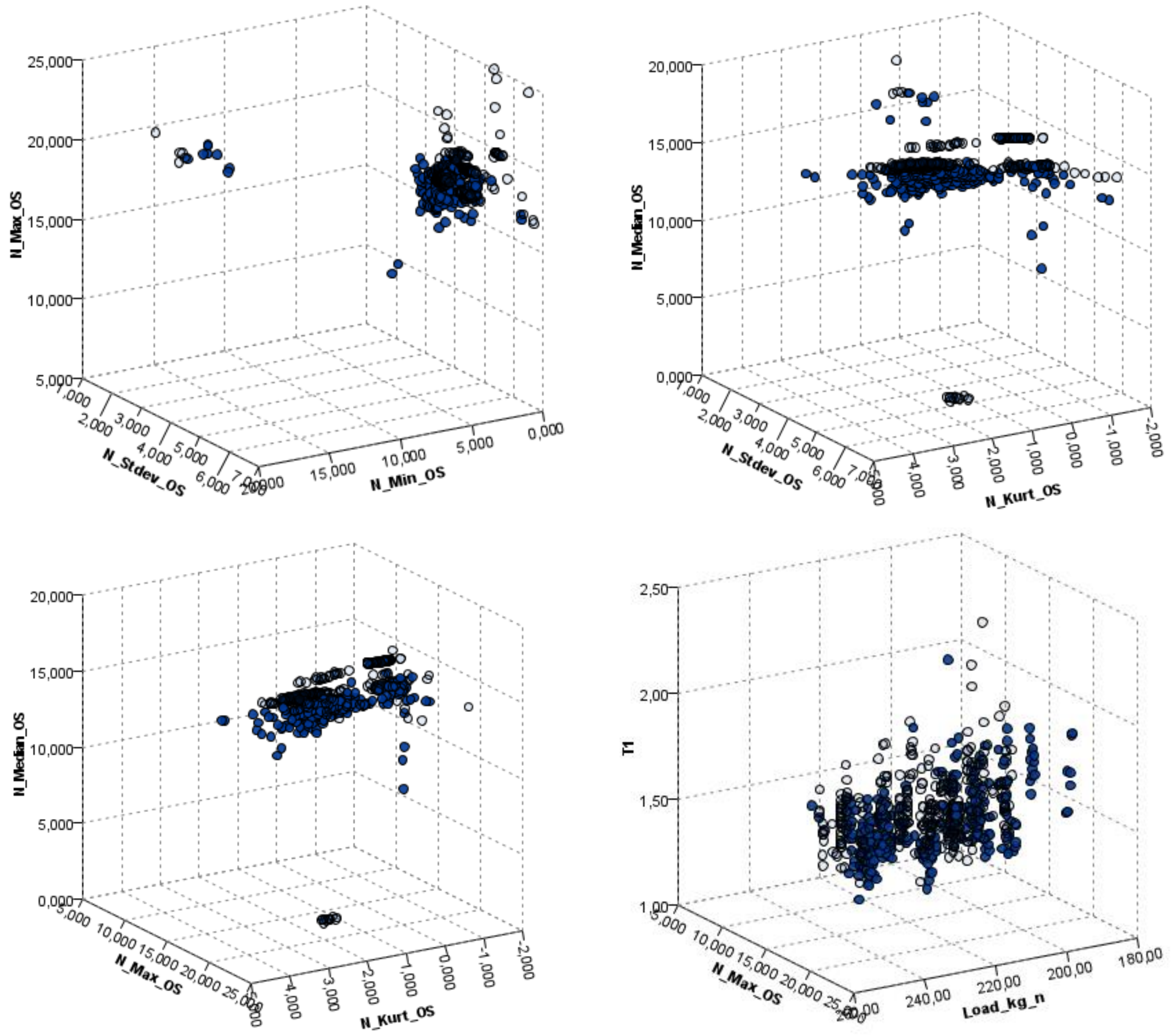


Figure 117. kNN Lower-dimensional projections of predictors at opening saddle position

Table 73. kNN classification matrix score for opening saddle position

Properties	None	Quasi-fault	Percent correct
None	338	19	94.7%
Quasi-fault	11	319	96.7%
Overall training percentage	50.8%	49.2%	**95.6%**
None	138	21	86.8%
Quasi-fault	6	129	95.6%
Overall testing percentage	49.0%	51.0%	**90.8%**

9.5.2 K-NN CLASSIFICATION ALGORITHM FOR IDLE SADDLE POSITION

Obtaining information regarding the classification of predictors, it can be seen that kNN works excellent in classifying data of idle saddle position (Figure 118). Since the data is not considered simple geometric (2D-3D) space but rather Cartesian coordinate (standardised) n-dimensional Euclidian space, the distance between points is calculated by absolute values of each subtraction and later squaring and rooting of the points to get a distance.

It can be observed with a lower-dimension 3D space that the best separation is achieved in combination with N_1Q_IS and N_StDev_IS variables, which are also, in previous ML models, the most important variables for label classification. The kNN, alongside ANN, shows the best classification performance of the given dataset (Table 74).

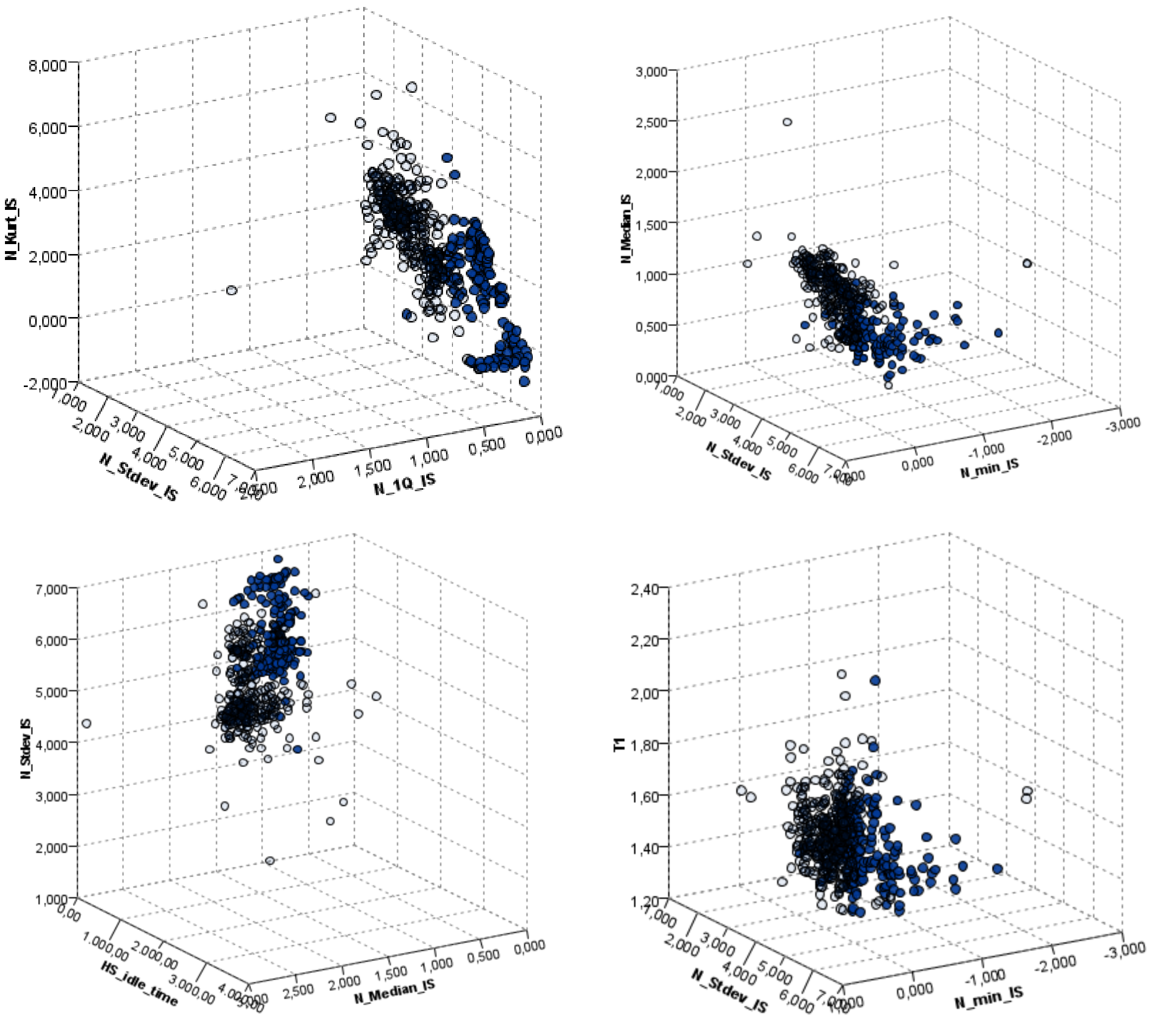


Figure 118. kNN Lower-dimensional projections of predictors at idle saddle position

Table 74. kNN classification matrix score for idle saddle position

Properties	None	Quasi-fault	Percent correct
None	341	14	96.1%
Quasi-fault	5	180	97.3%
Overall training percentage	64.1%	35.9%	**96.5%**
None	144	4	97.3%
Quasi-fault	3	81	96.4%
Overall testing percentage	63.4%	36.6%	**97.0%**

9.5.3 K-NN CLASSIFICATION ALGORITHM FOR CLOSING SADDLE POSITION

It can be seen that N_IQR_CS, Load_kg_n, N_RMS_CS and N_Mean_CS values are the most important ones and, as such, provides the most of the information for classifying in corresponding labels (Figure 119). Finally, performing classification of a dataset at the closing saddle position shows good prediction properties on the training data; however, when kNN was performed on testing data, a significant reduction in accuracy was noticed (Table 75). Although data show a somewhat moderate prediction of the "None" label, the data is prone to underfitting since the proportion of samples is relatively small for training and testing at the closing saddle position, which could be further improved and compared in the analysis.

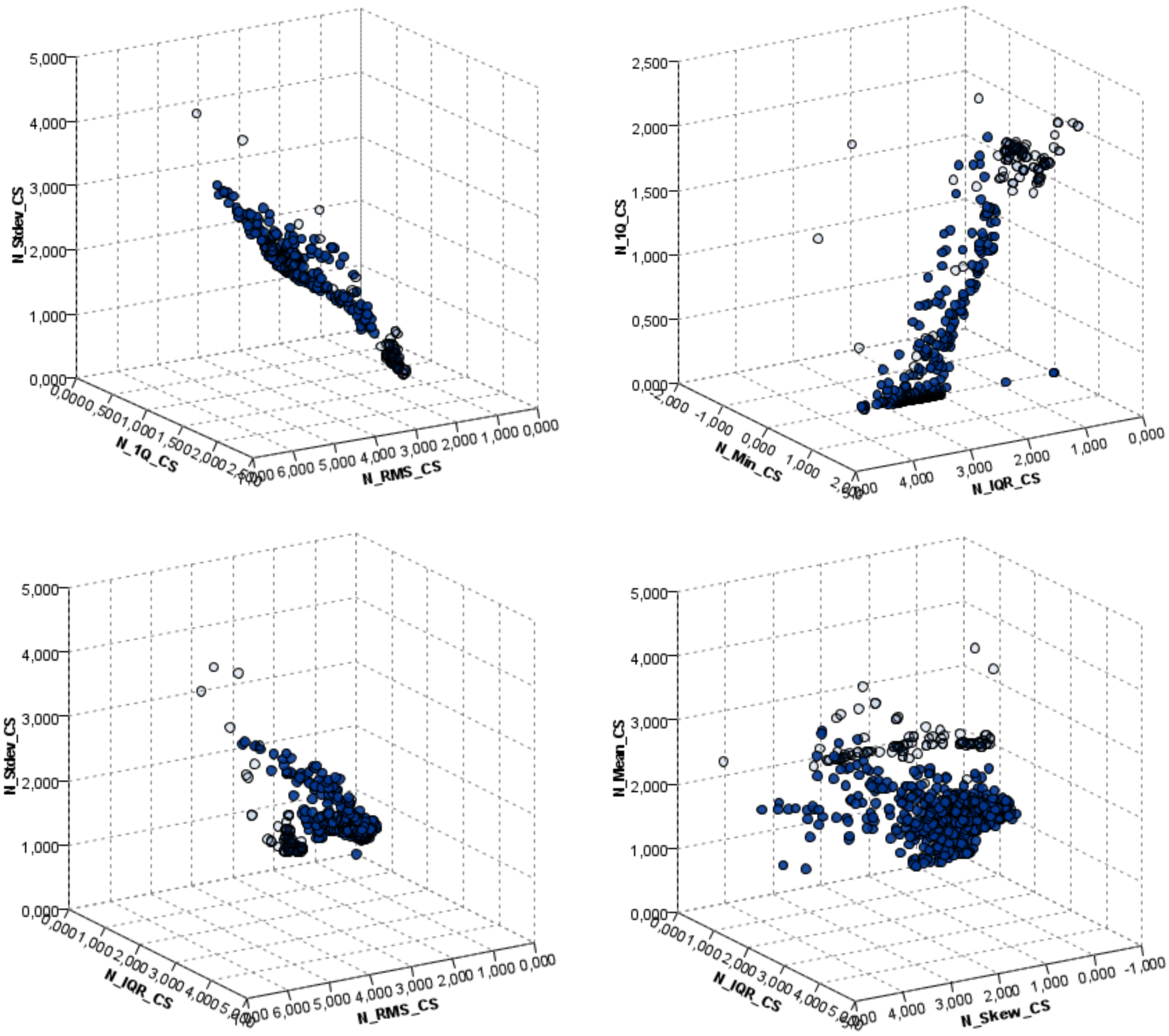


Figure 119. kNN Lower-dimensional projections of predictors at closing saddle position

Table 75. kNN classification matrix score for closing saddle position

Properties	None	Quasi-fault	Percent correct
None	109	19	85.2%
Quasi-fault	16	520	97.0%
Overall percentage	17.9%	82.1%	**94.7%**
None	54	19	74.0%
Quasi-fault	9	194	95.6%
Overall percentage	22.8%	77.2%	**89.9%**

9.6 MACHINE LEARNING CLASSIFICATION RESULTS AND DISCUSSION

After evaluating hypothesis space for the selection best ML model suitable for classification, the most effective separation was achieved by ANNs (Figure 120). Namely, after observing all the possible positions in detecting normal operating states from non-normal or suggested "Quasi-failure" with supervised learning methods, the results suggest that neural networks can discriminate observational (training) data in which the results and model outperform other approaches.

Table 76. Classification matrix for opening saddle position' data

	GNB		ANN		CART		LR		kNN	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
0	64%	65%	99%	95%	99%	94%	97%	92%	95%	87%
1	92%	87%	98%	94%	88%	86%	94%	82%	97%	96%
Σ_{op}	**78%**	**75%**	**99%**	**95%**	**94%**	**90%**	**95%**	**87%**	**96%**	**91%**

NOTE: 0 = None; 1 = Quasi-fault; Σ = Overall percentage classification.

Firstly, let us observe the results given in Table 76. Simple observation of results given by training data by each model infers a simple conclusion that data processing requires a non-parametric approach. Such inference can be obtained by the performance of the GNB model, which induces the primary assumption of data normality. However, if it requires data normality to be respected, it does not exclude a linear discriminant separation of non-parametric data. Therefore, using vector-discriminant analysis (e.g., SVM in Appendix 14) or "Support Vectors" in separating data labels shows poor prediction results. Even changing the hyperparameters (which was not conducted for model performance bias) shows that maximum accuracy of 94% at best was achieved by SVM. Therefore, using both parametric (simple ANN and LR) and non-parametric (CART and kNN), the results show that parametric, specifically ANN, shows the overall best performance in this case. Finally, it can be observed that kNN (Figure 120) shows the absolute best performance concerning the classification results of the "Quasi-fault" label, meaning that the kNN algorithm outperforms ANN and should be investigated further to see whether the classification is reasonable in the second case due to high accuracy of "Quasi-fault" labels.

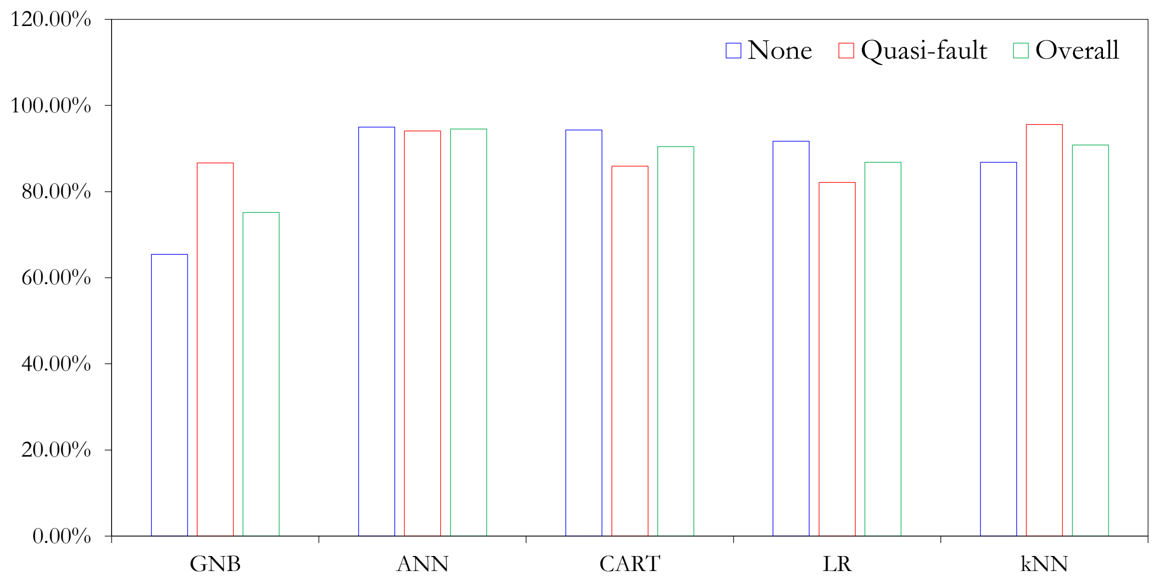


Figure 120. Classification results of ML algorithms' testing dataset at opening saddle position

Although the main idea of monitoring idle saddle position signal behaviour is to investigate the reaction time of hydraulic power signal (e.g., length and amplitude) for discovering anomalies in the signal, as such, cases with slow response and potential anomalies recorded during the experiment are labelled as suggested: "None" and "Quasi-failure". The results of classification show again that ANN show the best accuracy of classification (Table 77), while LR and kNN also show significant classification score.

Table 77. Classification matrix for idle saddle position' data

	GNB		**ANN**		**CART**		**LR**		**kNN**	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
0	64%	65%	100%	99%	94%	97%	97%	99%	96%	97%
1	92%	87%	99%	98%	92%	90%	96%	93%	97%	96%
Σ_{op}	**78%**	**75%**	**100%**	**98%**	**93%**	**94%**	**97%**	**97%**	**96%**	**97%**

Interestingly, every training ML model showed worse accuracy than achieved during training except ANN (Table 75), concerning the normal operating condition – suggesting that the sample for training was significant enough to model the system behaviour. However, split training and testing data (around 70-30%) impact the results since more proportion was given to the training of normal operating than faulty operating conditions.

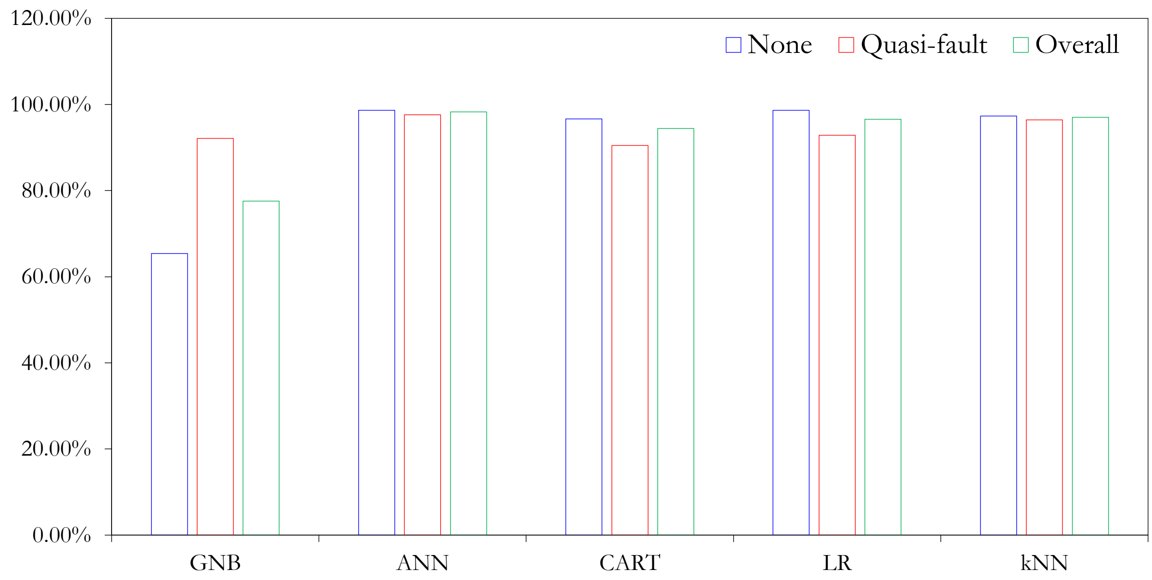


Figure 121. Classification results of ML algorithms' testing dataset at idle saddle position

Results for the opening saddle position show similarity in the consistency of kNN classification to follow up on the classification accuracy of ANN. Hence, it should be emphasized that both cost functions indicate close similarity scores of accuracy in the classification matrix; however, ANN outperforms in all cases.

Finally, observing classification scores at closing saddle position hydraulic power signal, the results of the classification cost function is given in Table 78, where ANN also outperforms other models.

Table 78. Classification matrix for closing saddle position' data

	GNB		**ANN**		**CART**		**LR**		**kNN**	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
0	64%	65%	92%	75%	70%	60%	72%	59%	85%	74%
1	92%	87%	100%	98%	100%	100%	99%	100%	97%	96%
Σ_{op}	**78%**	**75%**	**98%**	**92%**	**94%**	**89%**	**93%**	**89%**	**95%**	**90%**

The results of a classification in the last case show significant anomalies. Namely, only 17.9% (training) and 22.8% (testing) of normal operating condition data points were used for classification, concerning 82.1% (training) and 77.2% (testing) of quasi-fault data points were used for ML modelling. Therefore, the results show significantly higher accuracy of faulty label classification than normal operating conditions, suggesting that signal degradation (opening and closing saddle signal) unnoticeably influenced signal behaviour. The underlying reason for such classification could indicate that the separation of signal parts has changed over time under sensor replacement bias, suggesting a poor classification score of normal operating data points. However, although it concluded that bias exists after sensor replacement, such information could be beneficial in creating a new multiclass classification with unsupervised learning algorithms for detecting wear, leakage, degradation, and other faulty states. It will be used in the future thesis' author research.

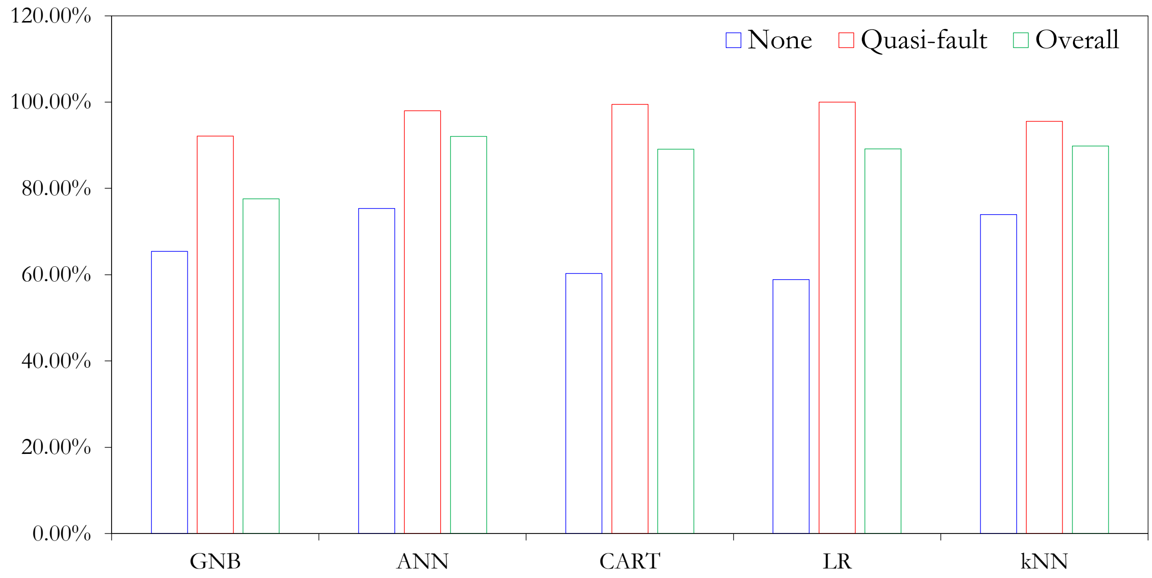


Figure 122. Classification results of ML algorithms' testing dataset at closing saddle position

Although models are only used as a first step in diagnostic procedures of EBM, the fact that up to 98% of classification was achieved creates a fundamental framework for creating an unsupervised model with association rules. The unsupervised learning methods will be used to associate the unknown degradation mechanisms by a specific method of association (e.g., simple correlation) with other variables (predictor) that show the highest association with the suggested one (e.g., elemental analysis of Fe and Cr increase) that could imply wear of a pump. It could be possible to discriminate further "Quasi-fault" labels into separate labels in such an instance. Discrimination is done based on the association of variables with potential degradation mechanisms expressed in n-fold-change (e.g., mean, median, standard deviation, IQR etc.).

10 RELIABILITY ANALYSIS

The reliability analysis using FP are used to represent the FPMs change as time between events, as quasi-faults and normal operating conditions. The events in which FPM falls outside of the quality control range will be elaborated in the following chapter with practical analysis. The reliability analysis of the system is used with the Crow-AMSAA model for repairable systems with continuous usage. The model is designed to track the reliability within a particular test phase and not across test phases. The test, however, can be of equal or unequal length wherein each test or test interval Crow-AMSAA dedicates to reliability growth of a particular phase, assuming $t = 0$ for the beginning of the phase and $0 < S_1 < S_2 \ldots < S_n$ let be the time of modifications on components within test phase. Failure intensity λ_i can be assumed as constant between test periods (S_{i-1}, S_i) when changes are made to the system; hence, the number of failures N_{fi} during the ith period has a Poisson distribution with mean $\lambda_i(S_i - S_{i-1})$ as:

$$P(N_{fi} = n) = \frac{[\lambda_i \cdot (S_i - S_{i-1})]^n \cdot e^{-\lambda_i \cdot (S_i - S_{i-1})}}{n!}, \qquad n = integer\ value. \tag{10.1}$$

In this case, constant failure rate λ_i assumes TBF to be a constant following exponential distribution:

$$F(t) = 1 - e^{-\lambda_i t}\ t > 0. \tag{10.2}$$

Such a reliability growth model or Crow-AMSAA model will be used with the experimental industrial system (rubber mixing machine). However, the main idea is to use quasi-faults deteriorating boundaries as even times [1, 0]. It will be used as time-to-quasi-fault (TBQF) deviation events to prevent further system degradation from establishing the time between condition monitoring activities (TBCM).

10.1 RELIABILITY ANALYSIS OF RUBBER MIXING MACHINE

Usually, reliability analysis is utilised on mining machines with around-the-clock working regimes where time to an event is actually time between failures of such operating systems. The experimental study, however, includes the functional-productiveness markers FPMs as indicators of failure or quasi-failure events. Trend and serial correlation tests are used to evaluate the IID (independent and identical distribution) of MTBQF. The main idea behind these tests it to check whether TBQFs are IID, which is important later for selecting appropriate functions for reliability modelling. Secondly, evaluation and selection of best-fit distribution (AD and/or K-S test) are necessary for selecting the distribution parameters. The following equations are used for determining MTBQF:

$$MTBQF = \frac{\sum_{i=1}^{n} t_i}{n} = \frac{Sum\ of\ times\ to\ an\ event\ (T_{QF})}{Number\ of\ times\ to\ an\ event\ (N(T_{qf}))} \tag{10.3}$$

and failure rate:

$$\lambda_{QF} = \frac{1}{MTBQF}\ . \tag{10.4}$$

The FPMs i.e., predictors, from ANN model will be selected as TBQF variables for estimating reliability. Hence, each of the variables at the opening saddle (Table 79), idle saddle (Table 80) and closing saddle (Table 81) is used to determine quasi-fault time-to-an-event (i.e., TBQF) and to determine reliability function.

Table 79. ANN variance importance at opening saddle position

Variable	Importance	Normalized importance
N_Stdev_OS	0.199	100.0%
N_Median_OS	0.127	63.7%
N_Min_OS	0.154	77.5%
N_Kurt_OS	0.122	61.1%

Table 80. ANN variance importance at idle saddle position

Variable	Importance	Normalized Importance
T3	0.116	65.3%
N_Stdev_IS	0.115	64.8%
N_1Q_IS	0.177	100.0%
N_Kurt_IS	0.126	71.2%

Table 81. ANN variance importance at closing saddle position

Variable	Importance	Normalized Importance
N_Stdev_CS	0.162	81.0%
N_Mean_CS	0.200	100.0%
N_RMS_CS	0.127	63.6%
N_Min_CS	0.186	93.1%

Since the main idea is not to use failures as time-to-an-event or time-between-failures as binary variables [0 = normal, 1 = fault] but rather a quasi-fault degradation estimation, the same principle will be used under the assumption of quasi-fault states on a same manner [0 = None; 1 = Quasi-fault]. Therefore, on the same principle as estimating event failures, the quasi-faults can be considered "left and right-censored" events (failures). Depicted in Figure 123 (left), the results show that the first cycle showed a quasi-fault "event" at the start of the experiment, although with a stable process later on. Following the principle of functional-productiveness, the boundaries set different thresholds later in the experiment Figure 126 (right).

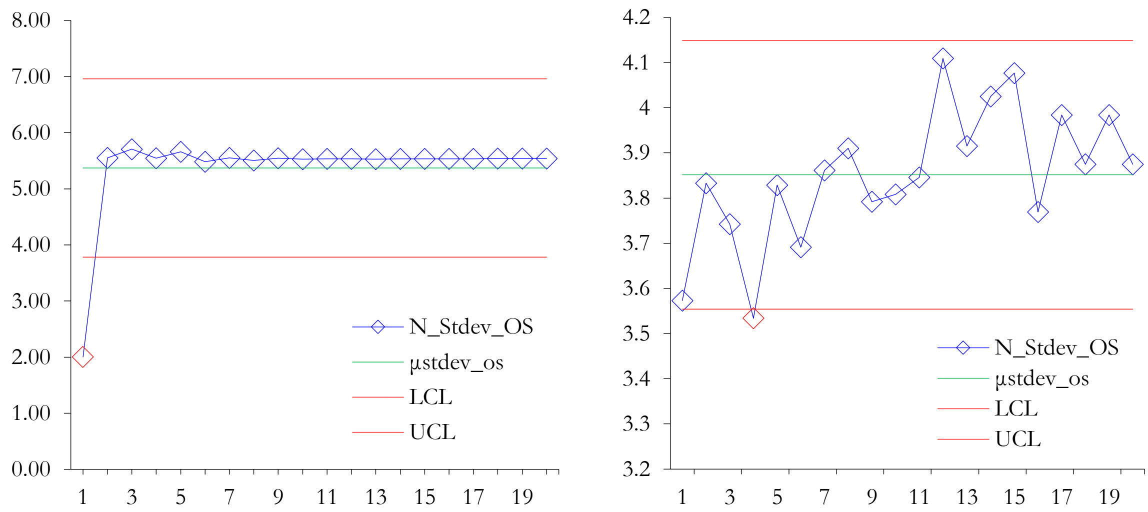


Figure 123. N_StDev_OS at the first 20 cycles (start of the experiment)

10.2 Trend and correlation test analysis

Before starting the reliability analysis, the assumption of IID needs to be valid. Hence, this will be accomplished by utilising the Mann-Whitnney-U test statistic using the equation:

$$U = 2\sum_{i=1}^{(n-1)} ln\frac{T_i}{T_{i-h}} \quad . \tag{10.5}$$

where T_i is the failure time at $i = 1, 2 \ldots$n, and index h is also given at $h = 1, 2 \ldots n\text{-}1$. Using U statistic, the goal is to determine the presence, in this case, of a trend between compared variables, failure with lag 1, 2...n. The calculated value at the first four lags is done with 5% (0.05) confidence intervals, and the results are given in the table:

Table 82. Mann-Whittney *U*-test statistic results

Variable	No. events	DOF	*p*-value (U test)	Status	Method
$TBQF_{i-1}$	202	402	0.8732	Not rejected	Renewal process

The resulting Mann-Whittney test statistics show no trend in the data; hence, the observations do not reject the null hypothesis. After trend analysis, the author of the thesis used both graphical representations to search for the presence of correlation between *i* and the *i*-1 to *i-4* lag quasi-fault data (Figure 124). In addition, both autocorrelation tests (Figure 125) and partial autocorrelation (Figure 126) were used to check for correlation between the events of *i-th* lag. There was no correlation between TBQF and the associated lag variable detected.

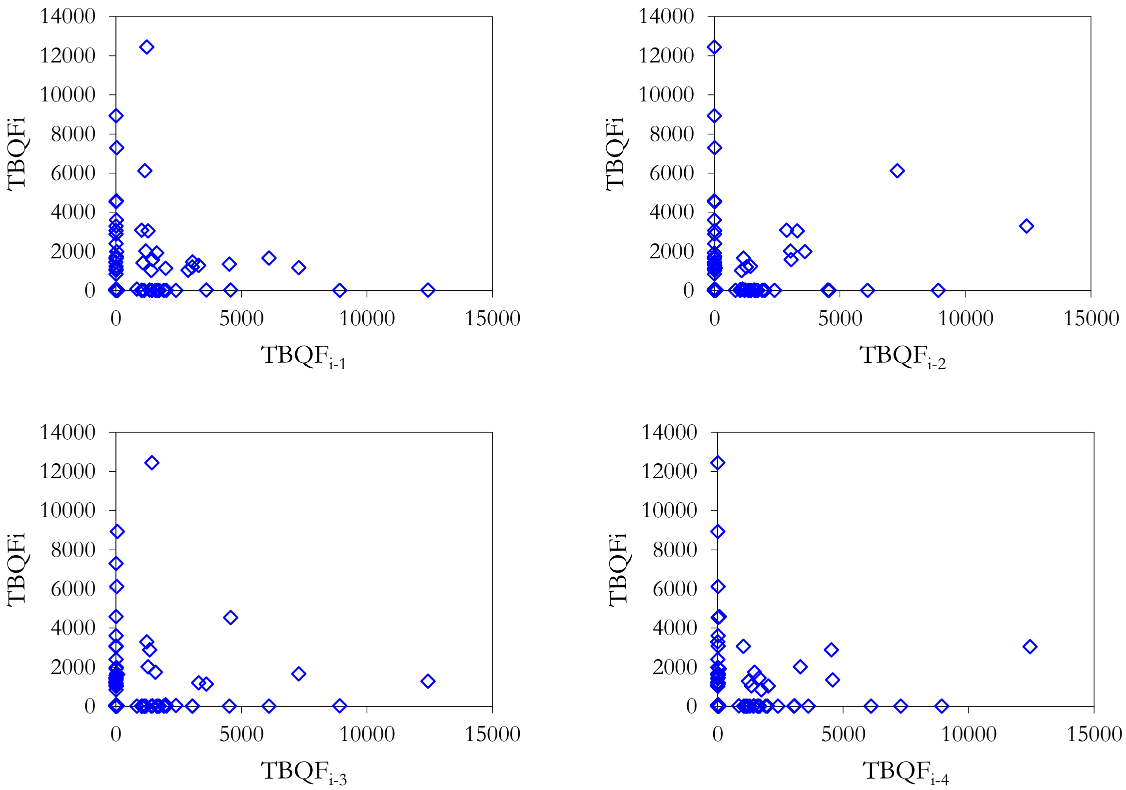


Figure 124. Correlation test of rubber mixing machine hydraulic control system

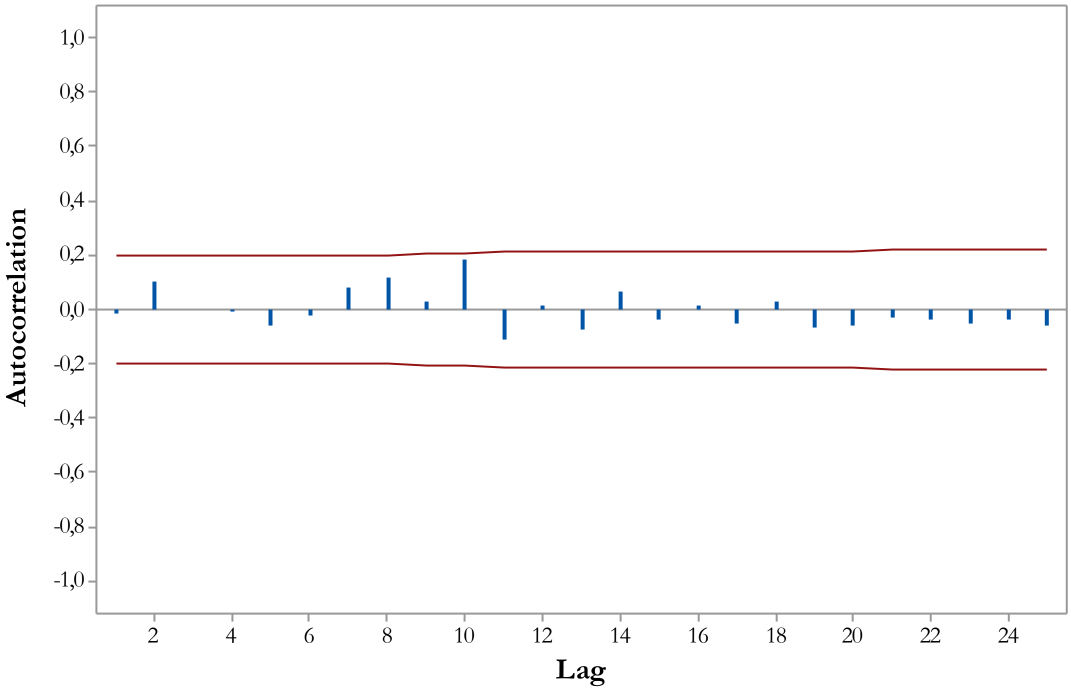


Figure 125. Investigating the presence of autocorrelation

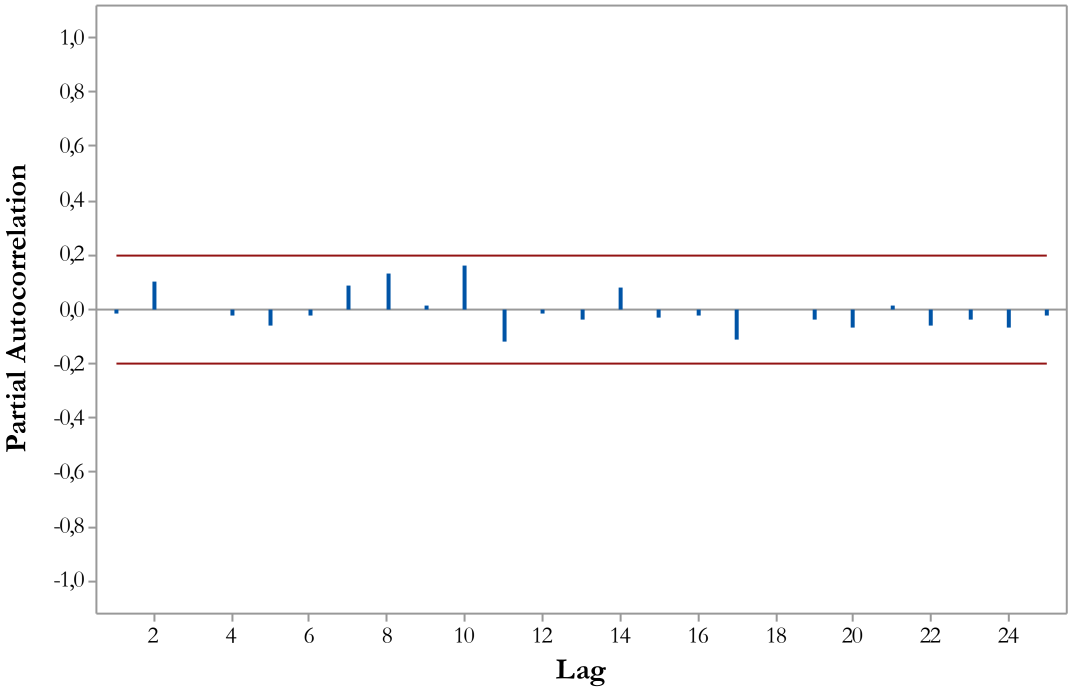


Figure 126. Investigating the presence of partial autocorrelation

10.3 Distribution estimate and reliability function

The goodness of fit test using EasyFit software for TBQF show five best-fitted distributions using the Kolmogorov-Smirnov (K-S) test (Table 83). All of the distribution parameters are given in Table 84, of which Weibull (3P) function parameters are used in the reliability modelling, and the cumulative probability function is given in Table 83.

Table 83. Goodness-of-fit for the five most ranked distributions of TBQF

Distribution	Kolmogorov-Smirnov	
	Test statistic	**Rank**
Weibull (3P)	0.16551	1
Lognormal (3P)	0.17204	2
Pareto	0.18938	3
Beta	0.18940	4
Gamma (3P)	0.19054	5

Table 84. Parameters of the best-fitted distributions

Distribution	Lognormal		Pareto		Weibull (3P)			Beta		Gamma (3P)		
	μ	σ	α	β	α	β	γ	α	β	α	β	γ
HyPower	2.906	3.841	0.32	1.98	0.295	139.68	1.98	0.164	0.179	0.2004	2144.6	2.0

The reliability function calculation for the lognormal distribution is given as:

$$R_{hypower}(t) = e^{\left(-\left(\frac{t-\gamma}{\beta}\right)^{\alpha}\right)} \tag{10.6}$$

where t represents the time, γ represents the location parameter; β models the shape of a curve as noted as the shape parameter; and α is the scale parameter of the 3P-Weibull distribution. Hence, substituting values into eq.(10.6) from Table 84, we get:

$$R_{hypower}(t) = e^{\left(-\left(\frac{t-1.9833}{139.68}\right)^{0.29487}\right)}. \tag{10.7}$$

The resulting reliability shows that the system is highly sensitive to disturbances, since already at around 2500 minutes (~40 hours), the system needs to be checked for anomalies and deviations based on the quasi-fault determined thresholds, as it showed to be the case during the experiment.

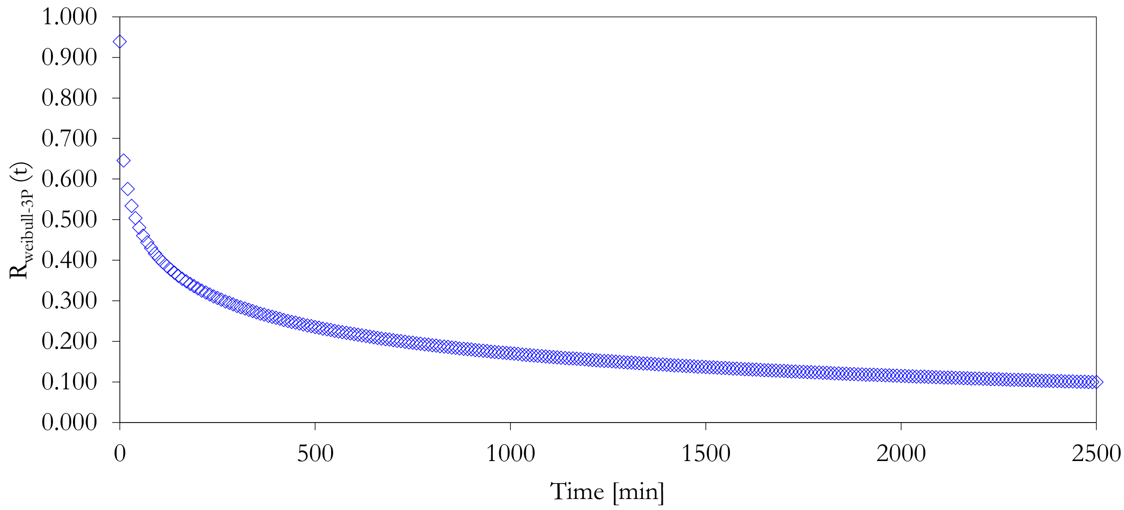


Figure 127. Reliability function using Weibull-3P distribution parameters

Since the research only considers hydraulic power data of a rubber mixing machine, it suggests an even shorter inspection time is required. Using all the probability distribution functions presented (top 4 ranked), the reliability function of each of the models shows similar 10% of event values range from 2490 hours – suggested by Weibull-3P distribution (Figure 127) – to 3655 hours – suggested by BETA distribution (Figure 128). Considering that Weibull-3P is the most accurate one in terms of fit, the inspection time should be set at around 2000 hours.

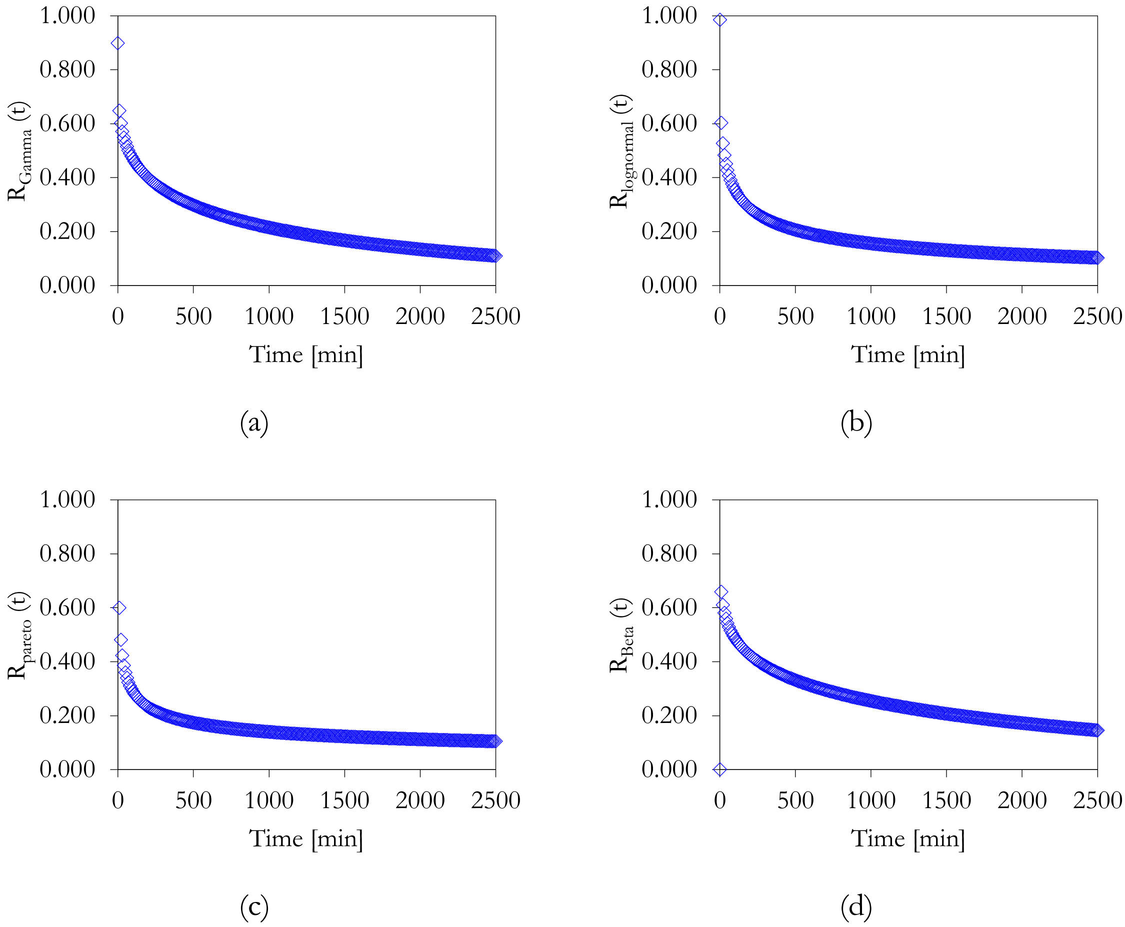


Figure 128. Reliability functions: 3P-Gamma (a); 3P-Lognormal (b); Pareto (c); and Beta (d)

Considering that the process shows significant variation throughout the experiment, considering the anomalies within the variables extracted from the observation during the experiment, it would be interesting to see the process behaviour using SPC stability analysis. However, the author is set this objective to investigate in future studies and will be beyond the scope of the present research.

Although reliability analysis is in its early stages with this type of research, the author decided to draw a line on the work here. The following studies will include in-detail reliability analysis using FPMs to establish the “functional-productiveness process quality” as a time-between-quasi-fault (TBQF) as a way to determine the actual maintenance quality of a specific machine and the machine behavior itself. In such way, it will be possible to follow up the machine process by comparing different machine reliabilities.

Chapter IV

"Knowing yourself is the beginning of all wisdom."

Aristotle

11 DISCUSSION

The lack of EBM manifesto acknowledgement spurs the philosophy behind the research. The author argues the benefits of implementing EBM practice in the era of sustainably-technological ecosystems. By accepting the EBM paradigm, theoretical gains could be of immense importance since already imposed Green Deal initiatives justify the rationale. The author also believes that the maintenance practitioners will immensely gain from EBM in all spheres of maintenance – diagnosis, prognosis and optimisation. However, indeed it presents a thin line between operational and maintenance performance. Based on the current body of existing evidence, the probability of gaining genuine results is relatively high. A discussion on the outcome of the thesis research will be given in the following.

11.1 MAINTENANCE RESEARCH THROUGH EU PROJECTS

From critical appraisal of projects' evidence, the results seemingly lack impact and achievement, even in highly developed countries. Reflecting on the current maintenance research within the EU project framework, one concludes that non-associated EU countries reflect the cause of slow maintenance advancement through narrative instead of practical propositions. Considering the primary mission of the Green Deal (achieving net-zero greenhouse emissions by 2050), sustainable maintenance initiatives are already being researched by various authors. By examining each industrial sector, the inference is that energy is the standard monetary value for every process. Therefore, energy-dedicated research firmly supports such initiatives and justifies the need for such a research agenda.

11.1.1 MAINTENANCE PROGRAMS ACROSS INDUSTRIAL SECTORS IN R&I PROJECTS

The CBM and PdM practices are different based on data utilised for decision-making – failure and control data – respectively. In recent years, projects dealing with control data are mostly situated in the manufacturing, energy, railway, and petroleum industry. Addressing the infrastructure and aerospace domain, SHM stands out the most. The underlying reason is that these applications' functionality strongly relies upon the health of the structures. The research of wind and nuclear power plants seems to be maintenance-research infants due to divided research interest in PdM, SHM, and PHM applications. The e-maintenance research is mostly described in the railways and aerospace industry, although no significant maintenance constructs were recognized apart from adding a communication dimension (remote monitoring) to assist maintenance actions.

A distinction of maintenance-related research across industrial sectors provides several important insights. Firstly, most of the research published relates to the PdM domain. Even so, papers cited in the domain of PdM that conducted a systematic review did not fully explain the protocol or underlying reasons for choosing particular eligibility criteria (e.g., time frame). Secondly, research on the PdM practice is mostly dedicated to the prognostic aspect (e.g. wind turbines), which can be a solution space for EBM research practice. An overview of existing maintenance practices and research focus on maintenance projects brought little to the table regarding the influence between energy and decision-making skills. The inconsistency of such verification must be firmly acknowledged and potentially subject to the future research agenda.

11.1.2 MAINTENANCE R&I PROJECTS SCIENTIFIC DELIVERABLES

An outline of the projects' dissemination activities, scientific deliverables and distribution of projects funded in the EU-FP is given for accomplishing the second research objective. The evidence suggests the lack of achievement in terms of patents (4.5%) and doctoral theses (3.9%), and on the contrary, shows the improvement of non-peer-review publications (5.9). One can question the validity of published reports in terms of peer-review assessment quality. Besides, after evaluating the CORDIS project factsheets, few or no workshops were organized in the non-associated EU countries. The thesis author states that technology transfer activities must be acknowledged as an activity in future research agendas.

Moreover, after reviewing projects' scientific deliverables, evidence shows that 25% of projects have produced a patent as a research deliverable, while less than 13% of projects have a doctoral thesis as a research deliverable, with one project having both results. The fact that only 42% of projects do not have a patent, thesis or a peer-review article, and 36% of projects do not have any scientific deliverable (PWF = 0) raises significant doubts about the actual impact on the advancement of industrial maintenance as a science considering funds invested into the research under the Framework Programme(s). Using Pearsons' correlation matrix, the author shows that the number of investments into the projects is strongly correlated to the project duration and the number of participants, regardless of the project type. We can see that projects with patents tend to produce more original scientific contributions as a primary research interest by addressing projects individually. However, projects with a thesis as a research deliverable tend to produce more book chapters and conference papers than peer-review journals, which would be expected considering the number of participants and funds invested in maintenance research.

Moreover, projects without patents and a thesis show excessive workshops and conference proceedings, suggesting low scientific impact for advancing maintenance in I4.0. Still, even though correlation can indicate tendencies within variables; however, it does not necessarily explain the causality between funds invested and scientific contribution. Therefore, the thesis' author conceptualised the Publication Weight Factor (PWF) to closely investigate all types of projects' scientific impact and contributions.

After setting a scientific quality assessment of research deliverables by PWF, the results show that for all projects, the average PWF equals (μ_{PWF}) 1.024. The individual PWF metric for projects shows the following. Projects with patents → $\mu_{PWF\text{-}PAT}$ =0.063; projects with thesis → $\mu_{PWF\text{-}DT}$ = 2.756; and projects without both → $\mu_{PWF\text{-}N\text{-}PAT/DT}$ = 0.578. The evidence suggests the following. The projects without a patent or thesis as an outcome show that average expenses account for about 5.6M€ per PWF. Compared to projects including doctoral theses (2.7M€/PWF), and projects with patents (1.2M€/PWF), it is two- and almost five-fold higher considering investments, respectively. Another interesting fact is that the more institutions are involved in the project activities, the more funds are spent, and on the contrary, the PWF is lower.

The fact that most productive projects include a single participant question the role of participants in improving PWF, i.e., producing scientific deliverables. Besides, out of all projects included for evaluation, 75% had a PWF less than 1.00. This evidence is compared using the same systematic methodology on a randomly selected project sample under "sustainable manufacturing" search strings on CORDIS to give a more objective assessment. The results show that projects in sustainability manufacturing have an average PWF of 6.0, which is almost six times higher than industrial maintenance projects with even lower investments (approx. 1.2M€/PWF). Indeed, the underachievements can be related to the poor technological development of industrial maintenance and the lack of involvement of eastern EU countries in industrial maintenance technology, thus potentially depicting the "Iron Curtain" dichotomy. Therefore, to increase the impact and scientific contribution to advancing industrial maintenance, more scientific support must be provided on the other side of the "Iron Curtain". This could be potentially spurred by including the sustainability aspect in industrial maintenance research, especially considering the EU Green Deal initiative.

Finally, with the evidence provided, excessive non-scientific contributions and lack of achievement of industrial maintenance research for I4.0 suggest literature saturation and the need for a new maintenance paradigm. The trade-off between investments and PWF of the projects' research outcomes to encourage sustainable ecosystem implementation depends primarily on the industrial maintenance impact and technological solutions. More meaningful solutions that can disrupt industrial and scientific schools of thought can be achieved by allocating more research resources for EBM research. As a result, higher PWF can be expected in industrial maintenance, especially considering the energy-dedicated and sustainable realm of maintenance philosophy.

11.2 ENERGY-BASED MAINTENANCE LITERATURE EVIDENCE

The current energy-dedicated maintenance research suggests that ongoing research efforts mostly include data-driven statistical and mathematical modelling for decision-making purposes [111]. The evidence points out that the relationship between energy consumption and maintenance availability is reciprocal [55], [135]; thus, monitoring energy parameters may provide insights into machine health and trigger preventive [109], [114] and corrective actions [113], [115]. In addition, it can also reduce carbon emission [57], improve diagnostic activities [116], [136], or even predict the future machine health (prognostics) [23], [24]. Although indicators such as EEI [108], [114], REEL [23], [24], RSL (Remaining Sustainable Lifetime) [111], ECP (Energy Consumption Profiles) [110], [137], or PWQ (Power Quality Monitoring) [138] are useful to evaluate machine health and system deterioration, they lack practical studies and verification on multi-component systems. Most of the studies verify proposed concepts on a single-unit system [23]–[25], [117] or by numerical simulations [113], [139]. Besides, it can be noticed that only a handful of studies [112], [116], [136], [140] specifically deal with fault diagnosis, while also some are concerned with prognosis using energy indicators as cost functions for optimisation purposes. In the following, the achievements of energy-dedicated research will be discussed, considering different levels of decision-making.

11.2.1 OPERATIONAL LEVEL OF MDM CONSIDERING EBM ACHIEVEMENTS

Research studies addressing MDM for determining fault and failure boundaries use degradation patterns in establishing thresholds or points of reference for triggering corrective or preventive actions at the operational level. However, determining fault and failure thresholds is far from an easy task, which is noticed in studies since most authors propose these boundaries randomly, subjectively or even by experience [136] due to the lack of empirical evidence of deteriorating mechanisms concerning energy consumption. Determining fault and failure thresholds is difficult because many variables affect energy consumption (flow, temperature, pressure, fluid density) [53], which is hard and time-consuming to model, especially in practice. However, ignoring energy-consumed fouling states without taking maintenance actions promptly [141] can lead to faulty operating conditions, which can rise to seven times higher cost and energy losses than operating in normal conditions [142]. Most studies set thresholds as static control limits, incoherent with components' degradation patterns in practice (e.g., seasonality in time-series decomposition). Hence, defining prognostic control limits [143], for instance, using an exponential weighted moving average (EWMA), could be more beneficial in detecting fouling effects of particular system units. By defining moving control limits in delineating functionality and failure thresholds, one can improve the quality of maintenance actions and react faster to signal deviations. Setting the control limit as the moving average, we consider it useful for quantifying the fouling effect, for instance, in reliability modelling [135]. By doing so, reliability based on energy fouling can be a more decisive factor in switching attention towards EBM research, which we are currently investigating.

11.2.2 TACTICAL LEVEL OF MDM CONSIDERING EBM ACHIEVEMENTS

Considering EBM achievements from the tactical standpoint of MDM, researchers are mostly dedicated to production losses caused by disturbances due to maintenance and operational activities. Although there are examples of studies examining the inherent relationship between maintenance and control engineering from an energy point of view [143], [144], there are no existing publications explicitly distinguishing operational and maintenance energy-monitoring signals, which are, in fact, hard to isolate.

Such studies are vital because operational elements (e.g., load) and maintenance actions (e.g., corrective) affect energy consumption simultaneously, thus causing an error in pattern recognition leading to flawed estimations in signal processing and difficulties in the decision-making process. To couple with this difficulty, the assumption is that the problem lies within the basic formulation of system functionality. The inability to quantify the fault or fouling effect of system degradation under various conditions as "true" or "false" causes problems in determining the functionality thresholds used for reliability estimation. Therefore, suggesting the notion of "functional-productiveness" for triggering maintenance actions (e.g. a limit of a minimal amount of products produced per time sequence) can be used over the traditional qualitative definition of functionality by providing quantitative time- and energy-saving windows.

By utilising the FP concept, one can isolate machine- and operator-induced energy consumption. Still, there is a considerable gap in monitoring energy data (e.g., energy efficiency, energy consumption, and consumption profile) [110]. Data mining procedures are usually used to monitor energy efficiency and detect anomalies for diagnosis. However, it is difficult to estimate the causes of anomalies, including technical (machine) and technological (human) errors, leading to more problems in assessing the root cause analysis in diagnosis. Statistical and mathematical modelling has been done by [23] and [139]. There are different propositions of formulation at the tactical (functional) level [24] for establishing functional limits. For instance, the EEI indicator is become useful in determining the amount of energy spent per product, and it is formulated as:

$$EEI^{\Sigma}(t) = \sum_{i=1}^{n} \lambda_t^{MDi} \omega_t^{MDi} E^{MDi}(t) \left[\frac{Wh}{product}\right]. \tag{11.1}$$

The pre-defined thresholds ($EEI_{threshold}$) are set for determining the Remaining Energy Efficient Lifetime (REEL), earlier explained as MREEL, QREEL.

Other propositional concepts are related to maintenance optimisation activities to preserve energy consumption, such as MEC. The MEC (Maintenance Energy Cost) is proposed by Mokhtari & Hasani [139] as a part of the Total Energy Cost (TEC) for operation and maintenance operations in flexible job-shop scheduling (FJSP) problem.

$$MEC = \sum_{i} \sum_{l} \sum_{p} Z_{il}^{p} e_m E_i^p \tag{11.2}$$

Where e_m represents the unit energy cost for maintenance operations, E_i^p energy consumption for maintenance operations, Z_{il}^p indicates whether pth maintenance operation is performed on lth maintenance interval of M_i (Z_{il}^p=1) or not (Z_{il}^p=0). Hence, mathematical modelling done at the operational level includes modelling the direct relationship between degradation and energy consumption patterns. In contrast, at the tactical level, models are done more on a statistical basis from a perspective of operational and maintenance activities with the aim of energy preservations in terms of optimising activities and not relying on monitoring energy consumption directly.

11.2.3 STRATEGICAL LEVEL OF MDM CONSIDERING EBM ACHIEVEMENTS

On-going energy-dedicated or sustainable maintenance research studies concerned with the research on a strategic level mostly deal with the energy aspect as an optimisation variable or an objective indicator [113], [114]. Both include the influence of maintenance activities and maintenance induced (energy) costs for determining optimal maintenance plans and optimisation activities [145]. Proposed models include actions ranging from corrective to predictive while reducing energy consumption and environmental impact [117]. The model is based on the Conservation Supply Curve (CSC), which in return, demonstrates the impact of maintenance and productivity for energy saving, and is mathematically formulated as:

$$CCE = \frac{I \cdot q + M\&O}{S} \tag{11.3}$$

given that *CCE* is the cost of conserved energy [$€/kWh$]; *I* is the capital cost in [€]; *M&O* is the annual change in *M&O* costs [$€/y$]; *S* is the annual energy savings [kWh/y]; *d* is the discount rate [-], and *n* is the lifetime of the conservation measure in [*years*], and *q* is the capital recovery factor [$years^{-1}$] and is modelled as:

$$q = \frac{d}{(1 + (1 + d)^{-n})}\ , \tag{11.4}$$

Three types of costs are included in *M&O* (total, variable, and unavailability costs). Thus, the model addresses energy efficiency and energy recovery potential by assuming three different maintenance policy scenarios (low, medium, and high). The *CCE* model shows that changing from CM to PdM approach can lead to almost tenfold $€/kWh$-saved and increase the performance by 10%.

Another strategic framework abstracted as Sustainable Condition-Based Maintenance (SCBM) is proposed by Senechal et al. [111]. The policy relies on the CBM approach to help maintenance decision-makers be more environmentally aware. The framework aims to avoid events that can cause environmental consequences, including the event of a product's failure. The authors also realised that defining triggering thresholds for maintenance actions has a more significant impact in SCBM than in traditional CBM, thus introducing the concept of RSL. Although the SCBM framework includes an element of energy for MDM, they go a step further by considering pollution as an environmental indicator, suggesting that it can have a significant effect in the eyes of the policy-makers to accept such radical change accepting sustainable maintenance policies.

Comparing sustainable- and energy-based maintenance with earlier maintenance policies at the strategic level, it can be concluded that choosing appropriate goals adds a dimension to sustainability and energy preservation. Hence, formulation and planning of maintenance activities are no longer focused on improving reliability, availability and maintainability but also on including the environmental factors. However, since the evidence from the three pillars used in this research, it can be seen that so far (until 2020), there have been no EU-funded projects or companies that have implemented this newly proposed paradigm. Since the EBM is in an infancy stage, it is expected that more scientific contributions in this domain, where the real benefits and setbacks can be acknowledged.

11.3 MAINTENANCE PRACTICE IN THE WEST BALKAN COUNTRIES

From the authors' knowledge, this is the first time that a questionnaire-based survey has been conducted on the territory of the West Balkan Penninsula regarding the maintenance of hydraulic machinery. The survey results show that many companies still rely on preventive and corrective maintenance practices while still performing corrective actions regularly, even with predictive technology. This is especially the case for mobile machines where failures happen at higher intensity. The data included both mobile and industrial machines, and for the appropriate realisation of the experiment, one such industrial machine was chosen for a practical case study. The overall results from descriptive statistics given from the survey analysis include meta-data that should be suggested to scientists or researchers performing controlled case studies on experimental hydraulic test-beds. The importance of such meta-data is elaborated in the following.

11.3.1 THE DESCRIPTIVE RESULTS OF MAINTENANCE PRACTICE

The benefits of using survey-meta are establishing the practicality of the proposed experimental design on one side while, on the other, gaining insight into the actual maintenance practice. Also, it is important for the practicality that parameters like NWP, NWF, oil type, viscosity type, the machine age, oil filling, and similar controlled variables be included in the design stage of the experiment. This way, researchers will have justifiable outcomes for disseminating their results.

Moreover, given the results, it was possible to determine the root causes of stoppages in hydraulic machines, which were formerly thought to be contamination. The outcome, however, proved that stoppages were actually due to overload and leakage. The root causes of failures in hydraulic machines are seemingly questioning the operators' control, maintenance activities and design of hydraulic machines. Such information is also beneficial since the proposition of energy-dedicated practice helps predict this kind of stoppages by energy monitoring activities. Besides, as the contamination is still one of the main causes of failures after overload and leakage, it is also used to determine the existence of multicollinearity between LCM practice and EBM monitoring practice, thus questioning the correlation between LCM practice, i.e., oil analysis variables (e.g., particles, elements) and hydraulic power variables (pressure and flow). The results show a low correlation coefficient between associated variables and the benefits of monitoring energy instead of oil contaminants for establishing binary classification.

Finally, the descriptive results of various maintenance practices show the following. The PdM practice shows the highest achievement of MTBF in terms of TBF averaging above 1500 hours. However, the results may be biased regarding machinery applied since most companies applying hydraulic control and predictive analytics are done on industrial machinery. The CBM and DM practice suggest good overall results with MTBF ranging between 1200-1400 hours alongside PdM. The important notice is that corrective maintenance, even though low nominal work factors (NWP and NWF), is important in MLR analysis. Therefore, another reason why investments in predictive analytics or condition monitoring practice should be realised. Besides, it is also shown that with higher power requirements, the MTBF is lower, and vice versa – suggesting that heavier machinery has a lower MTBF score even with higher MPPM. Therefore, the question raised is whether the amount of technicians per machine is important for improving MTBF or the predictive approach and intelligence.

The results show that maintenance practitioners and decision-makers rely on planned (preventive) maintenance activities or outsourcing maintenance activities. Even though companies utilise sensors for flow and pressure monitoring and temperature, they still rely on preventive maintenance actions, neglecting the health of a machine based on monitoring the parameters of hydraulic operation. Implementing EBM practice that relies on flow and pressure monitoring (hydraulic power) could be beneficial in diagnosis, prognosis and maintenance optimisation activities, thus supporting the thesis statements.

11.3.2 CONTAMINATION AS THE LEADING CAUSE OF FAILURES

One of the most important conclusions drawn from the practice is rejecting the null hypothesis that contamination is at least 70% responsible for stoppages in hydraulic systems. What contributed more to validating the thesis problem is the notion that overload, leakage, and temperature are all leading causes of failures that can be logically correlated with pressure and flow monitoring, thus energy waste. In addition, observing the correlation between energy input and MTBF further adds validity to achieving research benefits. This could be a missing link in drawing attention to maintenance research in MDM focused on observing hydraulic power (flow and pressure). Even so, it has been researched the correlation between particle contamination and hydraulic power and the results show a poor correlation factor ($p<0.05$). Therefore, by monitoring energy or contamination, there would be no collinearity between the results, therefore benefiting the use of monitoring hydraulic power consumption in determining the health status of hydraulic machines. In addition, by using hydraulic power as a variable, the goal in the following studies is to use association rules to determine, i.e., correlate with other potential fault or failure modes by setting multiple classification problems and exactly establishing diagnosis aiming at determining, for instance, wear, leakage, oil degradation, or similar root causes of stoppage.

The thesis aims to switch from using waste energy monitoring indicators given by the P-F curve of condition monitoring and switch from secondary energy, waste energy of temperature, vibration, etc., to the proposed primary energy monitoring procedure P-F curve. In such an instance, it could be beneficial because the use of easy to access and cheap flow control and pressure control sensors are widely available. However, the problem resides in machine learning and data analytics since the survey analysis is very low, considering analytical tools utilised in industrial maintenance. In addition, it also drags the question from the start of the thesis and brings us to the starting point: Can data analytics and feature engineering replace maintenance engineering? This question imposes several issues regarding the existence of maintenance as a scientific field. However, the important notice is that maintenance should dedicate more to utilising ML and Deep learning tools (e.g., unsupervised and reinforcement learning) for pattern recognition and improving decision-making.

11.3.3 IMPORTANT INDICATORS FOR IMPROVING OPERATIONAL PERFORMANCE

One of the key takeaways is the significance of maintenance intelligence versus maintenance personnel – questioning quality and quantity. This shows that with the use of sophisticated technology, such as in cases of predictive maintenance, which has no maintenance personnel, the results also show that such maintenance practice outperforms, for example, maintenance practices with specialists and engineers. It has been noted that the regression model shows that maintenance practice (as PdM) which has no personnel on the floor, no maintenance technicians or engineers, outperforms other maintenance practices in terms of MTBF. This further questions the imposed notion of "necessary evil."

Furthermore, it also poses threats to low- and mid-level maintenance departments (operational and tactical) since the I4.0 technology and cloud-based platforms for helping with maintenance decision-making can elbow out maintenance personnel – leading to more automation and digitalisation. One premise is that by going further into physics-of-failure, a valuable research field for forging Digital Failure Twins (DFT) on which modelling and optimisation can be done even without the presence of failure of a particular system. Opening such a chapter will require an enormous amount of data collected and a new field for maintenance as a science. Some of the key variables not seen so far in the experimental investigation are now included in the experimental study of the thesis while performing analysis and testing the model framework. For instance, oil refilling of the system can cause bias in estimating the results and performing oil analysis. Oil filling of the system (e.g., reservoir size) can cause potential deviation in results or even inaccurate estimation while reading performed spectrophotometric oil analysis in ppm.

12 CONCLUDING REMARKS AND FUTURE RESEARCH

12.1 GENERAL THESIS OVERVIEW

The thesis explains the need for an energy-dedicated maintenance platform as a response to the needs of enforced sustainability issues. The European Commission imposition reflects such issues through the Green Deal initiative. The primary goal of the Green Deal is to ensure decarbonisation and no net emissions of greenhouse gases by 2050. With such legislation, the author believes that the future of industrial maintenance research must reorient its focus toward sustainability goals. Such propositions have already been confirmed by an exponential rise of publications while latching on to the "Energy-oriented maintenance" and "Sustainable Maintenance" research titles. However, during the writing of the thesis, it was noticed that there was a rise in publications under such propositions; however, authors usually provide reports on optimisation and prognostic outcomes. The omission of the usage of energy variables for diagnostic purposes for determining the actual health state of machinery is still open for research contributions, where this thesis finds its contributions. To support such claims, the author of the thesis was dedicated to collecting evidence from three evidence pillars: state-of-the-projects, state-of-the-practice and state-of-the-literature followed by experimental verification.

The data collection process included an in-detail protocol for each pillar of evidence. Protocols are built upon Evidence-Based Practice, ensuring transparency and replicability of evidence collected. The reason for such a systematic approach was provoked by the inability to replicate the process of data collection from other studies, especially secondary source literature. In addition, each protocol includes a quantitative assessment of data collected and the validity of reports by eligibility criteria. Since no study was dedicated to investigating research contributions in terms of EU projects, the author proposed a systematic and transparent protocol for extracting such evidence. Such research provided insights on industrial maintenance's current maintenance manifesto within the EU research domain. Besides, it also confirmed the lack of maintenance advancements and sustainability aspects in maintenance research, which can be considered a strong argument supported by the rise of literature publications without funding of such kind. The research regarding the maintenance practice highlighted the importance of predictive analytics and the lack of sophisticated maintenance technology in improving MPIs. In addition, the empirical evidence from the practice highlighted the benefits of switching from corrective and preventive to the condition and predictive maintenance.

The data collected from aforementioned three pillars of evidence also served as an apparatus to acknowledge the upside of EBM practise contributions. Namely, it was established that most of the decision-makers, regardless of decision-making level (operational, tactical and strategic), rely on static thresholds. By proposing such a claim, it can be perceived that managers and engineers comprehend indicators as static decision-making boundaries in determining the health of the system state, consequently conducting appropriate maintenance activities in returning the system to a healthy state. As a response to such philosophy, the author of the thesis proposes dynamic boundaries conceptualised as functional-productiveness markers (FPMs). Such markers are extrapolated from continuous system behaviour, in this case, hydraulic power deviations, in which case the markers are determined via machine learning algorithms. The markers from hypothesis space are used for reliability analysis to better insight into triggering maintenance activities needed for reducing the uncertainty of the system, thus avoiding unnecessary stoppages. The implication of such an approach should paint a clear picture for managers, engineers and scientists in using energy (power) markers for diagnostic, prognostic and optimisation purposes since energy can be considered the main monetary value in production processes.

12.2 CONTRIBUTION TO THE LITERATURE

The diachronic nature of maintenance development has caused unnecessary confusion and complication with emerging concepts, which do not significantly alter maintenance philosophy. The maintenance development within I4.0 still relies on preventive and condition-based decision-making frameworks. By exposing these malleable concepts where actions need to be conducted only for the sake of productivity, neglecting sustainability indicators cause difficulties for maintenance to evolve. Such incoherence is seen in the claims that Cyber-Physical architectures (e.g. IoT maintenance) are the only drivers of maintenance evolution, and worse – the claim that such maintenance concept encapsulated the concept of "Maintenance 4.0" seems absurd. While shifting toward power consumption as a sustainable indicator where maintenance actions and activities are conducted based on energy deviation could be a potential argument for maintenance innovation. The future context of maintenance R&I and its impact on sustainability targets will significantly affect the manufacturing and production processes by advocating for such a holistic paradigm as EBM. With the proposed research pillars for extracting evidence, the conclusion is that industrial maintenance is shifting focus toward sustainable practice, thus adding a dimension to energy utilisation. This way, industrial maintenance will no longer be seen as a "necessary evil" but rather as a value creation function.

However, the EBM proposition can become onerous for a couple of reasons. Firstly, vague apprehension of failure mechanisms or omission of units' eigenfrequency and their power ports can consume time and error in the data processing. Secondly, the concept can be challenging to apply in rigid-service entities, such as a civil structure (e.g. bridges), on one side and the other on the inherent relationship between operational and maintenance processes. Finally, data scientists incorporating the EBM concept can be time-consuming and hard for training the models without the support of maintenance and process scientists. For instance, the function-productiveness concept with associated markers in determining potential degradation patterns took double the time of the experiment to gain insight into system behaviour considering low environmental disturbances. Therefore, using user-friendly softwares that do not require or has already been automatised would be beneficial in determining the same markers for classification purposes. In addition, fold-change (FC) could be a valuable online-monitoring tool for determining the effect of change given the environmental stressor.

Furthermore, the author of the thesis argues that more research studies should include transparent, evidence-based methodologies in extracting evidence to ensure validity and replicability in studies. It can also be beneficial in domains other than industrial maintenance to conduct a systematic analysis of research contributions by investigating EU research projects to gain a clearer insight into the state-of-the-art field of interest. It highlighted significant benefits and setbacks for the author of the thesis.

12.3 FUTURE RESEARCH

The future research includes going deeper into classification issues of system states by using unsupervised learning algorithms in determining potential root causes of degradation and faulty states. Namely, it has already been elaborated in the thesis that using Association Rules (AR) can increase the accuracy of establishing the exact root cause of failures by latching functional-productiveness markers to degradation mechanisms. That being said, it could be possible to establish diagnostics without prior knowledge of the system's failure mechanisms with AR by monitoring these markers, consequently triggering maintenance actions timely. With such a proposition, it could be possible to map sensitive points on machines (e.g., components, units, parts) and timely replace them without producing disturbances or affecting process quality.

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APPENDICES

Appendix 1. Hydraulic systems maintenance practice questionnaire-based survey

Question:	***Checkbox:***	
1. What is the number of employees in your company & what is the number of machines utilising oil-hydraulic control systems in your company?	**The number of employees in your company?** ☐ <50 ☐ 50-149 ☐ 150-249 ☐ 249-750 ☐ 750-1499 ☐ 1500-2499 ☐ 2500-5000 ☐ 5000-10000 ☐ >10000	**Number of aeroplanes employing oil-hydraulic systems?** ☐ 1-9 ☐ 10-19 ☐ 20-49 ☐ 50-99 ☐ 100-149 ☐ 150-299 ☐ 300-500 ☐ >500
2. Maintenance department size (including all levels of hierarchy within the company)?	**The number of maintenance personnel?** ☐ 5 ☐ 6-10 ☐ 11-15 ☐ 16-25 ☐ 26-50 ☐ 51-100 ☐ 101-250 ☐ 251-500 ☐ >500	**Staff of the maintenance department?** ☐ Technicians ☐ Laboratorians ☐ Engineers (BSc or MSc) ☐ Third-party personnel (external firm) ☐ Oil analysis experts (MSc or Spec.) ☐ Hydraulic system specialist ☐ Dr Eng. ☐ Other:___________________
3. Who does perform diagnostics and prognostics on your hydraulic machinery?	☐ Maintenance technician ☐ Maintenance BSc engineer ☐ Specialists (MSc degree) ☐ Specialists (Dr degree) ☐ External specialists ☐ Outsource company ☐ None ☐ Other (please specify): ____________________________	
4. What type of hydraulic control machines are utilised within your organisation (and how machines are you employing?	**4a. Industrial machines** ☐ Extruders: ☐ Casting machines: ☐ Paper production machines: ☐ Automated production lines.: ☐ Crushing machines: ☐ Textile production machines: ☐ Food and drink production: ☐ Elevators: ☐ Amusement park machines: ☐ Car production robots: ☐ Rubber mixing machines: ☐ Robot systems: ☐ Other: ____________________ **4c. Marine machines** ☐ Please specify:	**4b. Mobile machines** ☐ Tractors: ☐ Mine-drilling machines: ☐ Excavators: ☐ Manipulation equipment: ☐ Dampers: ☐ Tunnel boring machines: ☐ Rail equipment: ☐ Trucks: ☐ Road paving machines ☐ Oil-drillers: ☐ Other:_____________________ **4d. Aerospace industry:** ☐ Please specify:

5. What is the average nominal pressure within the hydraulic system?	**Pressure size systems** ☐ Low-pressure systems (<65bar) ☐ Low-to-medium pressure (65-140bar) ☐ Medium pressure systems (141-210bar) ☐ Medium-to-high pressure systems (211-350 bar) ☐ High-pressure systems (351-750 bar) ☐ Extreme-pressure systems (>750 bar)
6. What is the average flow within the hydraulic system?	**Flow type system** ☐ Low flow (1-20 l/min) ☐ Medium flow (21-55 l/min) ☐ Medium-high- flow (55-140 l/min) ☐ Light-High flow (141-320 l/min) ☐ High flow (321-1000 l/min) ☐ Extreme (>1000 l/min)
7. What types of fluid are you utilising?	**Mineral-based** ☐ HH – no additives ☐ HL – anti-corrosion, antioxidant additives ☐ HM – antiwear additives ☐ HV – viscosity improver additives **Fire extinguishing fluid** ☐ HFA – oil in water emulsion (water >90%) ☐ HFB – water in oil emulsion (water >40%) ☐ HFC – water glycol ☐ HFD - Synthetic fluid (phosphoric ester) **Environmentally accepted fluids** ☐ HTG – Vegetal base fluid ☐ HPG – Glycol base synthetic fluid ☐ HE – Esther base synthetic fluid ☐ Other: ____
8. What type of maintenance policy are you conducting in your company?	**Maintenance policy:** ☐ Failure-based maintenance (corrective maintenance) ☐ Time/use-based maintenance (preventive maintenance) ☐ Condition-based maintenance[3] ☐ Predictive maintenance[4] ☐ Opportunity-based maintenance[5] ☐ Design-out maintenance[6] ☐ Other: (*name please*) ________________________________
9. For a hydraulic control system machine, what specific analysis program do you conduct within maintenance policy?	**Oil monitoring program:** ☐ Visual monitoring of oil (colour, odour, other). ☐ Contamination Control Program (handling, filtering, monitoring, etc.). ☐ Oil Condition Monitoring (using APC, Aqua-Sensor, or another instrument for online monitoring). ☐ Used Oil Analysis Program (taking samples for off-line analysis into the lab – spectrometry, wear debris analysis, FTIR, TBN, TAN, etc.). ☐ Prognostics and health monitoring (vibration, ultrasound, thermovision camera, other). ☐ Other: (*name please*) ________________________________

[3] Using current component state information (signal and data processing) to conduct appropriate actions based on signals and data.

[4] Using current and prognostic information, like the remaining useful lifetime of components, to optimally schedule maintenance actions.

[5] The failure of one subsystem results in the possible opportunity to undertake maintenance on other subsystems (opportunistic maintenance).

[6] Design Out Maintenance aims to redesign those parts of the equipment which consume high levels of maintenance effort or spares cost or which have unacceptably high failure rates.

10. What system monitoring sensors are you using (check more boxes if necessary)?	**Sensors used for monitoring the hydraulic system:** ☐ Pressure sensors (transmitters, differential, electronic) ☐ Flow rate sensors (transmitters, switches, e-mechanical) ☐ Linear position sensors (for cylinder position) ☐ Contamination sensors (particle counters, water sensors) ☐ Oil condition sensors (e.g. ageing or mixing based on dielectric const.) ☐ Temperature sensors (transmitter, probes, e-switches) ☐ Angle sensors (rotation measurement on mobile machines) ☐ Ultrasound sensors ☐ None ☐ Other: (name please) ___________________________________
11. What type of instruments are you using for the oil contamination analysis program (check more boxes if necessary)?	**Oil monitoring instruments:** ☐ Automatic Particle Counters (APC) ☐ Metallic Contamination Sensor (MCS) ☐ Water (Aqua) Sensors ☐ Viscometers ☐ None ☐ Other: (*name please*) ___________________________________ **If you are using external oil analysis by laboratory (or you have your own) what instruments are utilized for elemental analysis in hydraulic oil:** ☐ FTIR (Fourier-transform infrared spectroscopy) ☐ ICP-OES/AES (Inductively Coupled Plasma/Atomic Emission) ☐ AAS (Atomic Absorption Spectrometry) ☐ AES (Atomic Emission Spectrometry) ☐ RDE-OES/AES (Rotating Disc Electrode) ☐ X-ray spectrometry ☐ None ☐ Other: (*name please*) ___________________________________
12. What mathematical or statistical tools are you employing for analysis and maintenance-decision making (check more boxes if necessary)?	**Mathematical/Statistical tools for maintenance decision making:** ☐ Regression analysis (least squares, linear, polynomial, etc.) ☐ Survival analysis (reliability theory, proportional hazard modelling, etc.) ☐ Decision tree analysis (FTA) ☐ FMEA (or FMECA) analysis ☐ Multi-criteria decision-making analysis (MCDM) ☐ Quality control charts (XR charts, XS charts, *p* chart, *u* chart, etc.) ☐ Mathematical modelling ☐ None ☐ Other: (*name please*) ___________________________________
13. How old is your hydraulic equipment (aeroplanes)?	☐ From 1 – 5 years no. machines:_ ☐ From 05 – 10 y. no. machines:__ ☐ From 10 – 15 y. no. machines:__ ☐ From 15 –20 y. no. machines:__ ☐ From 20 – 25 y. no. machines:__ ☐ From 25 – 30 y. no. machines:__ ☐ From 30 – 35 y. no. machines:__ ☐ From 35 – 40 y. no. machines:__ ☐ From 40 – 45 y. no. machines:__ ☐ From 45 – 50 y. no. machines:__ ☐ From 50 – 55 y. no. machines:__ ☐ From 55 – 60 y. no. machines:__ ☐ From 60 – 70 y. no. machines:__ ☐ Other or specific:___________
14. What is the average time between failures (TBF) of your hydraulic machinery?	**Time-between-failures in hours:** ☐ 0 - 100 hours ☐ 100 – 200 hours ☐ 200 – 300 hours ☐ 300 – 400 hours ☐ 400 – 500 hours ☐ 500 – 600 hours ☐ 1200– 1300 hours ☐ 1300 – 1400 hours ☐ 1400 – 1500 hours ☐ 1500 – 1600 hours ☐ 1600 – 1700 hours ☐ 1700 – 1800 hours

	☐ 600 – 700 hours ☐ 700 – 800 hours ☐ 800 – 900 hours ☐ 900 – 1000 hours ☐ 1000 – 1100 hours ☐ 1100 – 1200 hours	☐ 1800 – 1900 hours ☐ 1900 – 2000 hours ☐ 2000 – 2100 hours ☐ 2100 – 2200 hours ☐ 2200 – 2300 hours ☐ 2300 – 2500 hours ☐ Other: ________________
15. What are your hydraulic machinery's most common component failures (check more boxes if necessary)?	**Most common failure of components within the hydraulic system:** ☐ Hoses or pipes ☐ Actuator failure – hydraulic cylinder ☐ Actuator failure – hydraulic motor ☐ Pump failure ☐ Solenoid valve failures ☐ Proportional valve failures – directional valve ☐ Servo-valve failures – directional valve ☐ Electro-motor failure or ICE failure (for pump drive) ☐ Accumulator failure ☐ Sensors failure ☐ Filter failure ☐ Other: (*name please*) ________________________________	
16. What are the most common root causes of failure of your hydraulic machinery (check more boxes if necessary)?	**Most common root causes of failure:** ☐ Overloading the system ☐ Temperature (overheating the system) ☐ Inadequate oil in the system ☐ A mixture of the oil ☐ Oxidation of the oil (depletion of additives and viscosity drop) ☐ Contamination (particle contamination) ☐ Contamination (water and moisture) ☐ Maintenance personnel mistakes ☐ Seals ☐ Other: (*name please*) ________________________________	
17. What is the period for your filter replacement?	☐ 0-50 working hours ☐ 50-150 working hours ☐ 150-250 working hours ☐ 250-500 working hours ☐ 500-750 working hours ☐ 750-1000 working hours ☐ 1000-1250 working hours	☐ 1250-1500 working hours ☐ 1500-1750 working hours ☐ 1750-2000 working hours ☐ 2000-2500 working hours ☐ 2500-3000 working hours ☐ If you have precisely specified hours (days, with oil change, etc.), please specify the interval number or criteria:
18. What oil viscosity grade do you use in your machines (if you have a specific table for each of your systems, can you attach it?)?	☐ ISO VG 22 ☐ ISO VG 32 ☐ ISO VG 37	☐ ISO VG 46 ☐ ISO VG 68 ☐ ISO VG 100 ☐ ISO VG 150
19. How often do you refill the system with oil?	☐ After 25 hours ☐ After 50 hours ☐ After 60 hours ☐ After 75 hours ☐ After 90 hours ☐ After 100 hours ☐ After 125 hours	☐ After 150 hours ☐ After 200 hours ☐ After 250 hours ☐ After 300 hours ☐ After 500 hours ☐ After 750 hours ☐ Other (*please specify*):

20. What is the average time of complete oil change in your hydraulic machine, and based on which criteria do you conduct it?	**Average time of complete oil change:** ☐ After 100 hours ☐ After 150 hours ☐ After 250 hours ☐ After 500 hours (15 days) ☐ After 720 hours (monthly) ☐ After 1440 hours (after two months) ☐ After 2160 hours (quarterly) ☐ After 4320 hours (every six months.) ☐ After 8640 hours (yearly) ☐ Other (*please specify*):___________	**Criteria:** ☐ Routine ☐ Oil check ☐ Historical data analysis ☐ Contaminated oil ☐ Based on a suggestion from the equipment manufacturer ☐ The response of the system ☐ Other (*please specify*): ___________________________
21. What is the average oil filling of machines in your everyday usage, and how many litres/gallons/barrels do you spend monthly?	**Average machine oil filling:** ☐ <50 litres ☐ 50-100 litres ☐ 100-150 litres ☐ 150-200 litres ☐ 200-250 litres ☐ 250-300 litres ☐ 300-500 litres ☐ 500-1000 litres ☐ 1000-2000 litres ☐ 2000-3000 litres ☐ 3000-4000 litres ☐ Other (*please specify*):_________	**Hydraulic oil spent (litres/monthly)?** ☐ 0-500 litres ☐ 500-1000 litres ☐ 1000-2000 litres ☐ 2000-3000 litres ☐ 3000-4000 litres ☐ 4000-5000 litres ☐ Other (*specific number please add*): __________________________

Appendix 2. Results of oil analysis properties from laboratory

Property[1,2]	Method	Unit	No.0	No.1	No.2	No.3	No.4	No.5
Density[1]	ASTM 1928	[g/cm^3]	0.8635	0.8807	0.8804	0.8800	-	-
Flow point[1]	ASTM 92	[°C]	230	218	216	216	-	-
Flame point[1]	ASTM D97	[°C]	-32	-39	-38	-39	-	-
Viscosity 40°C[1]	ASTM D445	[cSt]	44.86	53.28	51.82	53.01	-	-
Viscosity 40°C[2]	ASTM D445	[cSt]	45.78	53.30	53.35	53.63	53.33	53.32
Viscosity 100°C[1]	ASTM D445	[cSt]	6.92	7.51	7.35	7.57	-	-
Viscosity 100°C[2]	ASTM D445	[cSt]	6.977	7.533	7.57	7.57	7.55	7.55
Viscosity index[1]	ASTM D2270	[-]	110	102	101	105	-	-
Viscosity index[2]	ASTM D2270	[-]	109	103	103	103	104	104
TAN[2]	ASTM D664	mgKOH/g	0.42	0.43	0.45	0.53	0.48	0.46
Water content[2]	ASTM D6304	[ppm]	13	24	19	17	16	25
Zn	ASTM D4927	[%]	0.037	0.034	0.034	0.034	0.034	0.034
Fe	WDXRF	[ppm]	2	5	4	4	3	5
Pb	WDXRF	[ppm]	ND	ND	ND	ND	ND	ND
Cu	WDXRF	[ppm]	ND	ND	ND	ND	ND	ND
Si	WDXRF	[ppm]	27	24	29	18	20	27
Sn	WDXRF	[ppm]	ND	ND	ND	ND	ND	ND
Cr	WDXRF	[ppm]	1	1	1	1	2	2
Al	WDXRF	[ppm]	ND	ND	ND	ND	ND	ND
Ag	WDXRF	[ppm]	ND	ND	ND	ND	ND	ND
Ni	WDXRF	[ppm]	3	ND	ND	ND	ND	ND
Mn	WDXRF	[ppm]	ND	ND	ND	ND	ND	ND
Cd	WDXRF	[ppm]	ND	ND	ND	ND	ND	1

[1,2] Fluid analysis samples are taken and sent to two different laboratories for information collection.
ND = Not detected.

Appendix 3. ISO 4406:2017 code for contamination level

ISO 4406 code	Number of particles per ml	
	Lower number	**Higher number**
24	80 0000	160 000
23	40 000	80 000
22	20 000	40 000
21	10 000	20 000
20	5 000	10 000
19	2 500	5 000
18	1 300	2 500
17	640	1 300
16	320	640
15	160	320
14	80	160
13	40	80
12	20	40
11	10	20
10	5	10
9	2.5	5
8	1.3	2.5
7	0.64	1.3
6	0.32	0.64

Appendix 4. Measured values per cycle of workload and intensity data

20 Cycles measured @		Work Load and intensity				
n	**Date**	**Pre_cycles**	**Prod_cyc [daily]**	**HS_Time**	**HS_idle**	**[kg] per 20n**
165	6.10.2021	165.0000	355.0000	398.4200	3897.5800	4067.8700
432	7.10.2021	267.0000	374.0000	632.7300	5173.2700	4315.1500
818	8.10.2021	386.0000	388.0000	477.8900	7263.1100	4376.6800
2897	14.10.2021	2079.0000	393.0000	400.4400	3606.5600	4645.6000
3257	15.10.2021	360.0000	434.0000	393.0200	5966.9800	4684.4000
4443	18.10.2021	1186.0000	370.0000	393.0200	5242.9800	4654.5500
4740	19.10.2021	297.0000	401.0000	393.0200	6098.9800	4768.4800
5191	20.10.2021	451.0000	386.0000	902.5300	5316.4700	4080.6800
5544	21.10.2021	353.0000	330.0000	410.8000	3044.2000	4777.0500
5915	22.10.2021	371.0000	335.0000	696.8800	4445.1200	4336.5600
6137	23.10.2021	222.0000	317.0000	392.8000	5427.2000	4999.6000
6600	24.10.2021	463.0000	319.0000	393.0100	2501.9900	4415.4000
6823	25.10.2021	223.0000	274.0000	421.0500	3158.9500	4261.0000
7090	26.10.2021	267.0000	351.0000	404.4700	2250.5300	4418.0000
7413	27.10.2021	323.0000	394.0000	980.5300	4077.4700	4525.3000
7931	28.10.2021	518.0000	404.0000	498.4700	6474.5300	4326.1000
			...			
10014	3.11.2021	240.0000	398.0000	406.2570	2792.8730	4700.8000
11975	9.11.2021	1961.0000	323.0000	401.7458	1928.0442	3990.6000
12381	10.11.2021	406.0000	317.0000	397.0440	2611.3860	4169.6000
12432	11.11.2021	51.0000	407.0000	409.1640	1181.1460	3902.6400
12951	12.11.2021	519.0000	259.0000	397.5640	2760.3460	4560.6000
13232	13.11.2021	281.0000	404.0000	396.4320	3212.3030	3879.7000
13760	14.11.2021	528.0000	378.0000	458.0102	1605.5498	4180.4000
14021	15.11.2021	261.0000	331.0000	414.6004	2144.6796	4170.5300
14547	16.11.2021	526.0000	428.0000	398.7597	1877.7303	4591.6500
14901	17.11.2021	354.0000	418.0000	396.4197	2242.4103	4510.5700
15256	18.11.2021	355.0000	387.0000	399.5838	2807.3062	4445.9200
15636	19.11.2021	380.0000	442.0000	404.9458	2605.5542	4184.5100
16226	20.11.2021	590.0000	416.0000	621.2916	1658.8384	4194.2000
19126	29.11.2021	2900.0000	388.0000	440.6909	2786.7491	4764.7000
19466	30.11.2021	340.0000	339.0000	406.1911	2229.0889	4279.8000
19761	1.12.2021	295.0000	297.0000	403.4309	1907.4091	4690.0000
20150	2.12.2021	389.0000	338.0000	408.4415	2488.9785	4671.0100
20434	3.12.2021	284.0000	355.0000	386.9453	2261.5847	4193.2000
20845	4.12.2021	411.0000	405.0000	385.4499	2561.5701	4486.8700
21485	6.12.2021	640.0000	339.0000	380.0810	2342.2690	4058.4400
21839	7.12.2021	354.0000	353.0000	386.9215	2024.7685	4048.5000
22846	10.12.2021	1007.0000	394.0000	384.2151	2151.2249	4378.6000
23670	11.12.2021	824.0000	426.0000	380.9267	2559.9733	4701.7900
23690	12.12.2021	20.0000	273.0000	384.6666	2001.6234	4166.4400

Appendix 5. Automatic particle counter and aqua sensor (saturation) data

20 Cycles measured @		Automatic Particle Counter data				Aqua Sensor	
n	**date**	**APC4**	**APC6**	**APC14**	**TEMP_CS**	**TEMP_AS**	**WatSat**
165	6.10.2021	20.3214	19.0611	16.5379	40.3761	42.2750	21.1000
432	7.10.2021	20.0675	19.1979	16.3172	38.3846	39.3550	22.3400
818	8.10.2021	20.0423	19.2092	16.2385	38.5868	39.0000	24.0000
2897	14.10.2021	20.5952	20.4693	17.4034	39.3769	39.5500	22.6750
3257	15.10.2021	20.6064	20.4851	17.1642	37.8354	39.3250	22.6250
4443	18.10.2021	20.6497	20.5131	17.4249	39.9084	40.4750	20.8750
4740	19.10.2021	20.8381	20.6057	17.5551	38.4056	40.1250	21.4000
5191	20.10.2021	20.6421	20.5570	17.5260	39.9275	38.6000	23.5250
5544	21.10.2021	20.6839	20.5103	17.4014	39.9618	42.1750	20.4250
5915	22.10.2021	20.8461	20.6459	17.3402	40.1221	41.8250	21.1000
6137	23.10.2021	20.8589	20.7211	17.3053	39.2128	36.8750	25.9750
6600	24.10.2021	20.6774	20.4776	17.0673	38.2791	38.0500	23.9500
6823	25.10.2021	20.6511	20.5143	16.7519	37.5545	40.9500	20.2000
7090	26.10.2021	20.6892	20.4497	16.6523	38.1757	42.8750	18.7500
7413	27.10.2021	20.7899	20.5215	16.7317	37.9123	38.4000	22.1250
7931	28.10.2021	20.7743	20.5300	16.6879	38.5982	40.0750	20.9250
8361	29.10.2021	20.9959	20.4946	16.6110	39.0842	42.7250	19.0000
8679	30.10.2021	21.3780	20.5834	16.6226	40.4554	42.3500	19.8000
9074	31.10.2021	21.0138	20.6006	16.7058	37.2065	38.2000	22.8250
9304	1.11.2021	20.8140	20.4916	16.8483	38.3142	42.3000	19.0500
			...				
12432	11.11.2021	20.7242	20.5000	16.6667	37.1268	40.8000	21.0250
12951	12.11.2021	20.7569	20.5008	16.6276	37.6511	37.4750	24.6250
13232	13.11.2021	21.0838	20.5218	16.6297	39.4703	40.7250	22.0500
13760	14.11.2021	21.1509	20.4964	16.6746	39.6742	42.9000	19.9250
14021	15.11.2021	20.9766	20.4879	16.6984	38.1303	41.8000	20.5750
14547	16.11.2021	21.0824	20.4416	16.7541	39.0762	41.6250	20.9750
14901	17.11.2021	21.0819	20.4673	16.8000	38.4915	41.1500	21.3000
15256	18.11.2021	20.9674	20.4356	16.8121	37.8696	40.7250	21.7250
15636	19.11.2021	21.0664	20.4702	16.6445	37.8894	40.0750	21.9500
16226	20.11.2021	21.2404	20.5673	17.0353	40.0510	43.2750	19.7500
19126	29.11.2021	20.8439	20.4683	16.6030	38.1175	41.2250	21.3250
19466	30.11.2021	20.6939	20.4590	16.5505	36.6457	39.5250	21.8000
19761	1.12.2021	20.9026	20.5393	16.6467	37.8467	40.8000	20.9000
20150	2.12.2021	21.0633	20.5159	16.7366	38.7098	38.8000	22.9500
20434	3.12.2021	20.9252	20.5022	16.6405	37.8558	38.9000	22.7750
20845	4.12.2021	20.9252	20.5022	16.6405	37.8558	38.6750	22.3750
21485	6.12.2021	20.6357	20.5057	16.6871	35.3616	39.2000	21.8250
21839	7.12.2021	20.6511	20.6231	16.6876	35.5717	38.8500	22.0500
22846	10.12.2021	20.5319	20.4841	16.6267	35.1362	39.5250	20.1750
23670	11.12.2021	20.5632	20.4912	16.2550	35.2132	35.6250	24.0750
23690	12.12.2021	20.5339	20.4978	16.7280	34.1999	37.7250	22.4750

Appendix 6. Power delivery to the system per specific sum of cycles and daily

20 Cycles @		Power delivery to the system [20 x n]			Power lost [%]	
n	Date	P [kWh/20cycles]	P_{lost} [%/20cycle]	P_{daily} [kWh/daily]	%20cycles	%daily
165	6.10.2021	0.8713	0.8713	15.4655	0.000%	0.000%
432	7.10.2021	0.8737	-0.0024	16.3383	-0.277%	-5.644%
818	8.10.2021	0.7964	0.0749	15.4499	8.597%	0.101%
2897	14.10.2021	0.7673	0.1040	15.0775	11.935%	2.509%
3257	15.10.2021	0.7646	0.1067	16.5918	12.246%	-7.283%
4443	18.10.2021	0.6979	0.1734	12.9109	19.903%	16.518%
4740	19.10.2021	0.6850	0.1863	13.7345	21.380%	11.193%
5191	20.10.2021	0.7363	0.1350	14.2105	15.494%	8.115%
5544	21.10.2021	0.6853	0.1860	11.3073	21.348%	26.887%
5915	22.10.2021	0.7070	0.1643	11.8422	18.857%	23.428%
6137	23.10.2021	0.6980	0.1733	11.0638	19.885%	28.461%
6600	24.10.2021	0.6608	0.2104	10.5406	24.153%	31.845%
6823	25.10.2021	0.6900	0.1813	9.4536	20.803%	38.873%
7090	26.10.2021	0.6843	0.1870	12.0090	21.465%	22.350%
7413	27.10.2021	0.7068	0.1645	13.9241	18.878%	9.966%
7931	28.10.2021	0.7083	0.1629	14.3086	18.702%	7.481%
8361	29.10.2021	0.6990	0.1723	13.6309	19.772%	11.862%
8679	30.10.2021	0.7022	0.1691	13.4815	19.411%	12.828%
9074	31.10.2021	0.7434	0.1279	9.7384	14.680%	37.032%
9304	1.11.2021	0.7241	0.1472	13.2870	16.895%	14.086%
			...			
12432	11.11.2021	0.6948	0.1765	14.1383	20.261%	8.581%
12951	12.11.2021	0.6869	0.1844	8.8952	21.165%	42.484%
13232	13.11.2021	0.6643	0.2070	13.4187	23.758%	13.235%
13760	14.11.2021	0.6594	0.2119	12.4629	24.318%	19.415%
14021	15.11.2021	0.6737	0.1976	11.1492	22.682%	27.909%
14547	16.11.2021	0.6699	0.2014	14.3351	23.118%	7.309%
14901	17.11.2021	0.6739	0.1974	14.0850	22.652%	8.926%
15256	18.11.2021	0.7155	0.1557	13.8459	17.875%	10.472%
15636	19.11.2021	0.7403	0.1310	16.3608	15.033%	-5.789%
16226	20.11.2021	0.8238	0.0475	17.1346	5.453%	-10.793%
19126	29.11.2021	0.7460	0.1253	14.4730	14.377%	6.417%
19466	30.11.2021	0.7578	0.1135	12.8452	13.022%	16.942%
19761	1.12.2021	0.7102	0.1611	10.5470	18.485%	31.803%
20150	2.12.2021	0.7558	0.1155	12.7729	13.256%	17.410%
20434	3.12.2021	0.7411	0.1302	13.1549	14.940%	14.940%
20845	4.12.2021	0.7439	0.1274	15.0634	14.624%	2.600%
21485	6.12.2021	0.6876	0.1837	11.6550	21.081%	24.638%
21839	7.12.2021	0.6621	0.2092	11.6864	24.007%	24.436%
22846	10.12.2021	0.6887	0.1826	13.5676	20.956%	12.272%
23670	11.12.2021	0.6518	0.2195	13.8832	25.193%	10.231%
23690	12.12.2021	0.6561	0.2152	8.9558	24.698%	42.092%

Appendix 7. Interpolation equations for dealing with missing values

Property	Equation	R^2
Fluid density	$y = 7E\text{-}15x^3 - 3E\text{-}10x^2 + 4E\text{-}06x + 0.8637$	0.9855
Viscosity @40°C	$y = 2E\text{-}12x^3 - 1E\text{-}07x^2 + 0.0016x + 45.038$	0.9658
Viscosity @100°C	$y = 6E\text{-}14x^3 - 4E\text{-}09x^2 + 8E\text{-}05x + 6.9355$	0.9397
Viscosity index [-]	$y = 1E\text{-}16x^4 - 1E\text{-}11x^3 + 3E\text{-}07x^2 - 0.0031x + 110.05$	0.9543
Flame point [°C]	$y = -5E\text{-}12x^3 + 2E\text{-}7x\text{^}2 - 0.0035*A2\text{^}1 + 229.76$	0.9799
Flow point [°C]	$y = -2E\text{-}12x^3 + 1E\text{-}07x^2 - 0.0014x - 32.116$	0.9766
Water [ppm]	$y = 1E\text{-}11x^3 - 4E\text{-}07x^2 + 0.0038x + 13.076$	0.9510
Zn [ppm]	$y = 369.54x^{-0.009}$	0.9842
Fe [ppm]	$y = 0.000000000003*A2\text{^}3 - 0.0000001*A2\text{^}2 +0.001*A2 + 1.8297$	0.8952
Si [ppm]	$y = 7E\text{-}12x^3 - 2E\text{-}07x^2 + 0.0013x + 26.053$	0.4985
Cr [ppm]	$y = 1E\text{-}08x^2 - 0.0002x + 1.9884$	0.8762
Ni [ppm]	$y = 4.2538x^{-1.392}$	1.0000
TAN [mgKOH/g]	$y = -1E\text{-}14x^3 - 2E\text{-}10x^2 + 1E\text{-}05x + 0.4099$	0.7354

Where x = cycle number

Appendix 8. Autocorrelation and partial autocorrelation estimates of N_HyPower data

n	**ACF1**	**TSTA1**	**LBQ1**	**PACF2**	**TSTA2**
1	0.0013728	0.0195595	0.0003883	0.0013728	0.0195595
2	-0.0637644	-0.9085013	0.8421914	-0.0637664	-0.9085316
3	-0.0433429	-0.6150445	1.2330826	-0.0433385	-0.6174793
4	-0.0222836	-0.315621	1.3369232	-0.0264999	-0.377566
5	-0.0355053	-0.5026439	1.6018769	-0.0413982	-0.589833
6	-0.0627005	-0.8865406	2.432349	-0.0685318	-0.9764272
7	-0.03091	-0.4353632	2.6352067	-0.039282	-0.5596828
8	-0.0437372	-0.6154584	3.0434481	-0.058075	-0.8274421
9	-0.017305	-0.243058	3.1076858	-0.0319205	-0.4547965
10	0.0484969	0.6809675	3.6148168	0.0326676	0.4654413
11	-0.0548237	-0.7680534	4.2662741	-0.0712674	-1.0154035
12	0.0695247	0.9711892	5.3194366	0.0628845	0.8959662
13	-0.0155204	-0.2158042	5.3721966	-0.0308436	-0.4394543
14	0.0692142	0.9621691	6.4270169	0.0667718	0.951352
15	-0.0540087	-0.7473923	7.0727009	-0.059247	-0.8441404
16	0.0016481	0.0227444	7.0733054	0.0107546	0.153229
17	0.0314229	0.4336487	7.2942226	0.0263293	0.3751348
18	0.0722488	0.9961396	8.4684141	0.0816471	1.1632925
19	0.0068547	0.0940521	8.4790412	0.0123228	0.1755727
20	0.1103546	1.5140803	11.248405	0.1371907	1.9546666
21	-0.0586094	-0.7951984	12.033844	-0.046307	-0.6597727
22	-0.0581332	-0.7862928	12.810843	-0.0358148	-0.510283
23	-0.0612056	-0.8253394	13.676927	-0.0428369	-0.6103318
24	-0.0749278	-1.0070058	14.982146	-0.0859988	-1.225295
25	-0.0495715	-0.662922	15.556652	-0.0345575	-0.4923693
26	-0.0260325	-0.3473825	15.715986	-0.0463457	-0.660324
27	-0.0016675	-0.022238	15.716644	-0.0111475	-0.1588281
28	0.0358661	0.4783189	16.022545	0.0078813	0.1122919
29	-0.0021963	-0.0292578	16.023699	-0.0146701	-0.2090169
30	-0.0352185	-0.4691515	16.322063	-0.0894822	-1.2749257
31	0.0239778	0.3190659	16.461166	0.0223005	0.3177328
32	0.1636722	2.1768519	22.980505	0.1161467	1.6548364
33	-0.0684284	-0.8895739	24.12674	-0.0626278	-0.8923084
34	-0.0366222	-0.4742454	24.456997	-0.0306096	-0.4361203
35	-0.0456167	-0.5900687	24.972449	-0.0341883	-0.4871078
36	0.0239224	0.3089153	25.115057	0.0218771	0.3117008
37	0.0407089	0.525437	25.530509	0.0353085	0.5030689
38	-0.0139432	-0.1797234	25.579542	-0.012611	-0.1796788
39	0.0136644	0.1761007	25.626921	0.0306954	0.4373419

Appendix 9. Determining quasi-fault time-to-an-event (TBQF) at opening saddle position

TBQF [minutes]	Gate [1,0]	K_Bool	SD_Bool	MED_Bool	Min_Bool	Kurt_OS	SD_OS	MED_OS	Min_OS
2.117	1	0	1	0	1	1.492	2.003	17.427	11.267
0.000	0	0	0	0	0	0.780	5.551	17.467	2.558
0.000	0	1	0	0	0	0.344	5.707	17.366	2.452
0.000	0	0	0	0	0	0.530	5.544	17.337	2.558
0.000	1	1	0	1	0	0.166	5.657	17.261	2.437
0.000	0	0	0	0	0	0.785	5.48	17.401	2.562
0.000	0	0	0	0	0	0.614	5.548	17.339	2.568
0.000	0	0	0	1	0	0.664	5.505	17.318	2.568
0.000	0	0	0	0	0	0.571	5.546	17.331	2.564
0.000	0	0	0	0	0	0.639	5.53	17.351	2.576
0.000	0	0	0	0	0	0.641	5.531	17.342	2.573
				...					
0.000	0	0	0	0	0	1.503	4.259	13.847	1.476
0.000	0	0	0	0	0	1.728	4.112	13.957	1.932
0.000	0	0	0	0	0	1.544	4.215	13.788	1.65
0.000	0	0	0	0	0	2.083	4.129	14.094	1.401
0.000	0	0	0	0	0	1.779	4.101	13.66	1.451
0.000	0	0	0	0	0	2.092	4.084	13.912	1.765
0.000	0	0	0	0	0	2.115	4.095	14.002	1.885
0.000	0	0	0	0	0	1.586	4.314	14.057	1.433
0.000	0	0	0	0	0	1.662	4.223	13.992	1.807
0.000	0	0	0	0	1	1.977	4.166	14.137	2.145
0.000	0	0	0	0	0	1.505	4.314	13.957	1.361
0.000	0	0	0	0	0	1.886	4.243	14.32	1.35
0.000	0	0	0	0	0	1.768	4.267	13.986	1.186
0.000	0	0	0	0	0	1.719	4.231	14.05	1.462
0.000	0	0	0	0	0	2.036	4.184	14.004	1.438
0.000	0	0	0	0	0	2.250	4.094	14.203	1.456
0.000	0	0	0	0	0	2.120	4.186	14.402	1.583
0.000	0	0	0	0	0	1.838	4.11	13.974	1.507
96666.450	1	1	1	1	1	-0.192	1.41	13.463	9.825
0.000	0	0	0	1	0	2.260	3.67	12.887	1.593
0.000	0	0	0	1	0	2.584	3.531	12.458	1.291
96696.183	1	1	1	0	1	-0.399	1.361	14.063	10.421
0.000	0	0	0	0	0	2.249	3.782	13.025	1.313
0.000	0	0	0	1	0	1.959	3.632	12.797	1.357
0.000	0	0	0	0	0	2.102	3.666	13.09	1.489

Appendix 10. Determining quasi- fault time-to-an-event (TBQF) at idle saddle position

TBQF [min]	**Gate [1,0]**	**K_Bool**	**SD_Bool**	**MED_Bool**	**Min_Bool**	**Kurt_IS**	**SD_IS**	**MED_IS**	**Min_IS**
2.117	1.000	0	1	0	1	8.14	3.579	0.591	4.419
0.000	0.000	0	0	0	0	7.92	5.137	0.497	2.667
0.000	0.000	0	0	0	0	7.70	5.309	0.479	2.401
0.000	0.000	0	0	0	0	8.09	5.526	0.479	2.152
0.000	0.000	0	0	0	0	8.39	5.612	0.498	2.018
0.000	0.000	0	0	0	0	7.84	5.214	0.537	2.556
0.000	0.000	0	0	0	0	7.88	5.414	0.483	2.28
0.000	0.000	0	0	0	0	8.15	5.41	0.497	2.275
0.000	0.000	0	0	0	0	8.41	5.467	0.51	2.217
0.000	0.000	0	0	0	0	7.98	5.415	0.503	2.28
0.000	0.000	0	0	0	0	8.28	5.413	0.522	2.28
				…					
96666.450	1.000	0	1	0	1	8.5	4.145	0.406	1.898
0.000	0.000	0	0	0	0	6.78	5.242	0.58	0.062
0.000	0.000	0	0	0	0	7.35	5.245	0.295	-0.181
0.000	0.000	0	0	0	1	7.39	4.942	0.258	1.382
0.000	0.000	0	0	0	0	7.02	5.563	0.544	0.075
0.000	0.000	0	0	0	0	7.43	5.444	0.332	-0.315
0.000	0.000	0	0	0	0	6.97	5.426	0.552	0.009
0.000	0.000	0	0	0	0	7.19	5.273	0.433	-0.063
0.000	0.000	0	0	0	0	6.83	5.19	0.461	-0.196
0.000	0.000	0	0	0	0	7.58	5.169	0.47	-0.217
0.000	0.000	0	1	0	0	7.63	4.555	0.283	1.29
0.000	0.000	0	0	0	0	6.94	5.464	0.259	0.134
0.000	0.000	0	0	0	0	6.92	5.304	0.424	0.028
0.000	0.000	0	0	0	0	6.83	5.208	0.497	-0.142
0.000	0.000	0	0	0	0	7.17	5.301	0.506	-0.218
0.000	0.000	0	0	0	0	7	5.193	0.25	-0.248
0.000	0.000	0	0	0	0	6.73	5.321	0.395	-0.075
0.000	0.000	0	0	0	0	7	5.301	0.506	-0.218
0.000	0.000	0	0	0	0	7.34	5.193	0.25	-0.248
0.000	0.000	0	0	0	0	7.15	5.321	0.395	-0.075
0.000	0.000	0	0	0	0	6.76	5.172	0.592	0.211
0.000	0.000	0	0	0	0	7.06	5.211	0.35	-0.147
0.000	0.000	0	0	0	0	7.45	5.11	0.205	0.112
0.000	0.000	0	0	0	0	7.42	5.21	0.25	-0.047
0.000	0.000	0	0	1	0	7.53	5.509	0.138	0.089

Appendix 11. Determining quasi- fault time-to-an-event (TBQF) at closing saddle position

TBQF [min]	Gate [1,0]	K_Bool	SD_Bool	MED_Bo	Min_Bool	Kurt_CS	SD_CS	MED_CS	Min_CS
0.000	0.000	0	0	0	1	1.096	2.062	2.331	0.011
0.000	0.000	0	0	0	1	0.914	2.193	2.374	0.018
0.000	0.000	0	0	0	0	0.751	2.108	2.236	0.392
0.000	0.000	0	0	0	0	4.771	4.459	6.506	0.095
0.000	0.000	0	0	0	1	2.869	3.155	4.25	0.003
0.000	0.000	0	0	0	1	0.745	2.318	2.434	0.003
0.000	0.000	0	0	0	1	0.641	2.071	2.167	0.048
0.000	0.000	0	0	0	1	0.639	2.069	2.164	0.05
0.000	0.000	0	0	0	1	0.64	2.069	2.165	0.05
0.000	0.000	0	0	0	0	0.623	2.096	2.185	0.121
0.000	0.000	0	0	0	1	1.096	2.062	2.331	0.011
				…					
96672.317	1.000	0	1	1	0	1.29	0.92	1.58	0
96674.717	1.000	1	0	1	0	1.21	0.993	1.562	0
96696.183	1.000	1	1	1	0	1.195	0.921	1.505	0
96700.817	1.000	1	0	1	0	1.237	0.964	1.565	0
0.000	0.000	1	0	0	0	1.221	1.085	1.63	0
96710.983	1.000	1	1	1	0	0.516	0.13	0.53	0
0.000	0.000	0	0	0	0	1.235	0.957	1.559	0
0.000	0.000	0	0	0	0	1.247	0.946	1.562	0
0.000	0.000	0	0	0	0	1.237	0.967	1.566	0
0.000	0.000	0	0	0	0	1.184	0.901	1.484	0
0.000	0.000	0	0	0	0	1.308	1.116	1.716	0
0.000	0.000	0	0	0	0	1.241	1.006	1.594	0
0.000	0.000	0	0	0	0	1.24	0.954	1.56	0
0.000	0.000	0	0	0	0	1.25	0.961	1.572	0
0.000	0.000	0	0	0	0	1.246	1.031	1.614	0
0.000	0.000	0	0	0	0	1.203	0.979	1.548	0
0.000	0.000	0	0	0	0	1.25	0.961	1.572	0
0.000	0.000	0	0	0	0	1.246	1.031	1.614	0
0.000	0.000	0	0	0	0	1.203	0.979	1.548	0
0.000	0.000	0	0	0	0	1.252	0.873	1.523	0
0.000	0.000	0	0	0	0	1.233	1.002	1.585	0
0.000	0.000	0	0	0	0	1.231	1.035	1.605	0
0.000	0.000	0	0	0	0	1.284	1.027	1.64	0
0.000	0.000	0	0	0	0	1.186	1.087	1.605	0
0.000	0.000	0	0	0	0	1.264	1.077	1.657	0

Appendix 12. Interpolation graphs of physical and elemental oil analysis data

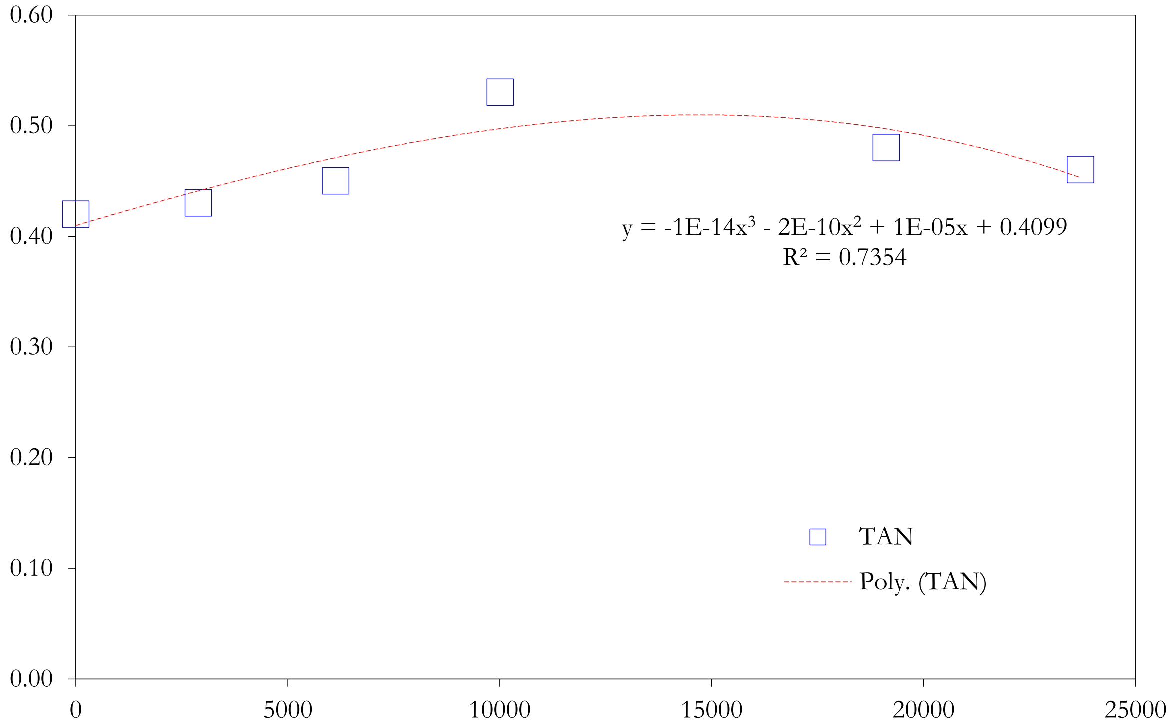

Figure 129. Data explanation of hydraulic cycles (x-axis) and TAN (y-axis)

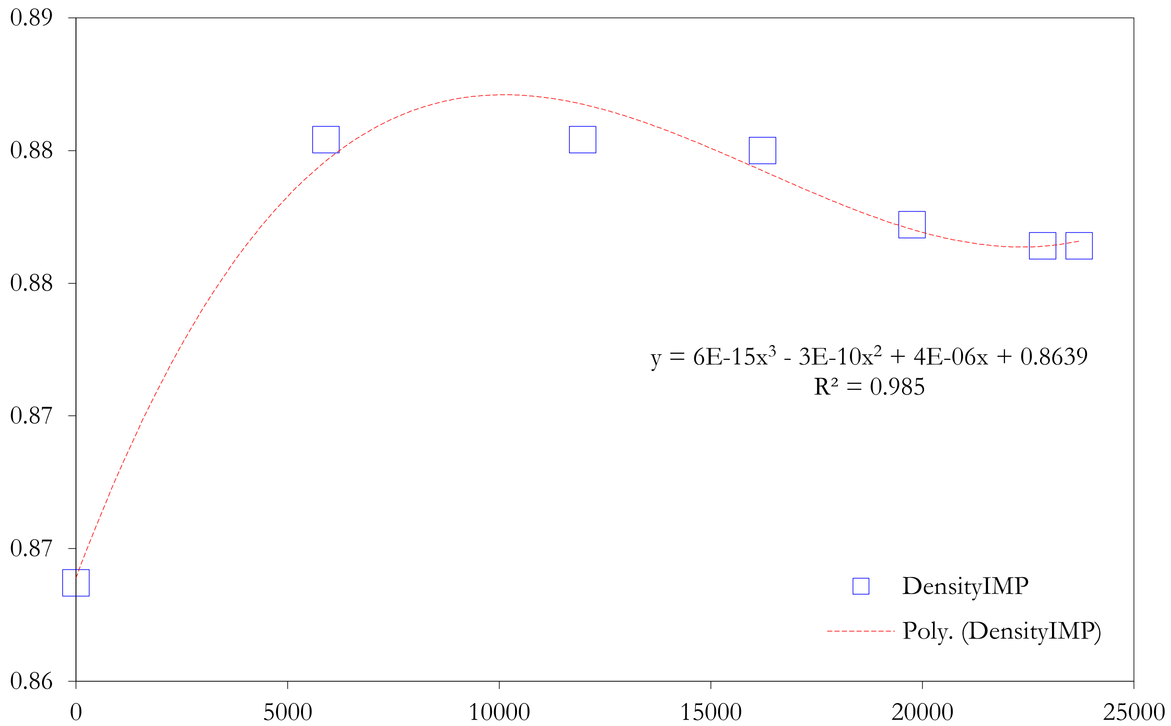

Figure 130. Data explanation of hydraulic cycles (x-axis) and density (y-axis)

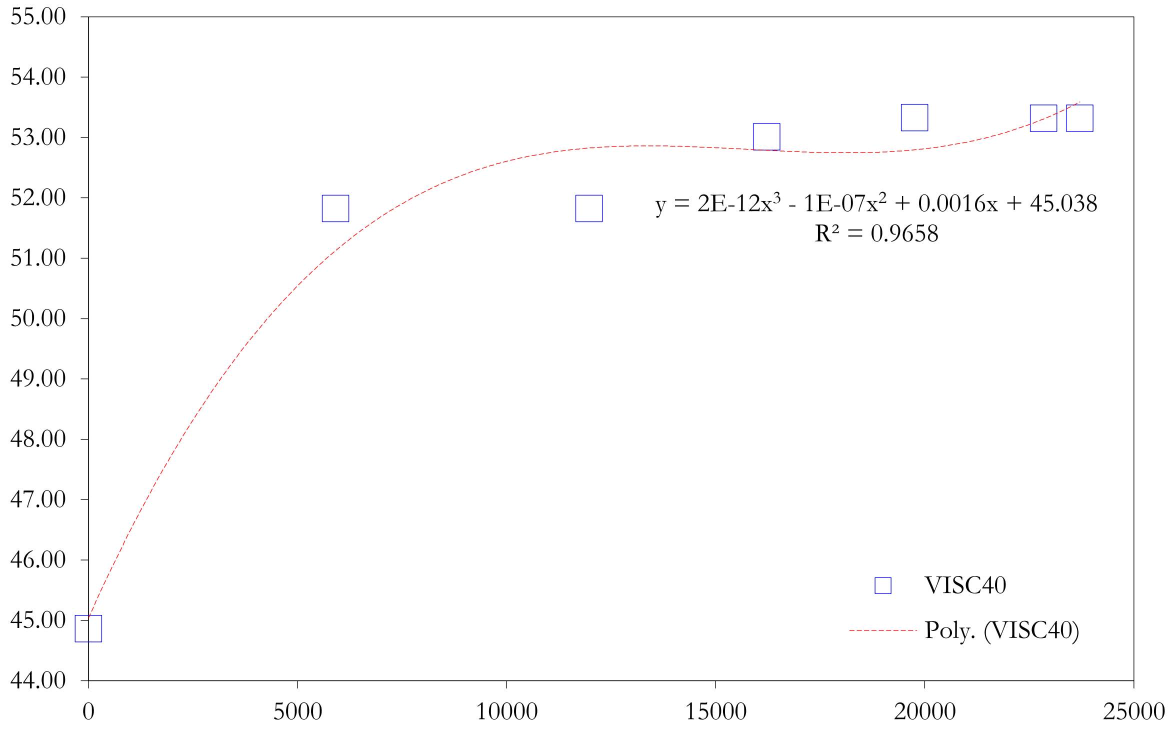

Figure 131. Data explanation of hydraulic cycles (x-axis) and viscosity 40°C (y-axis)

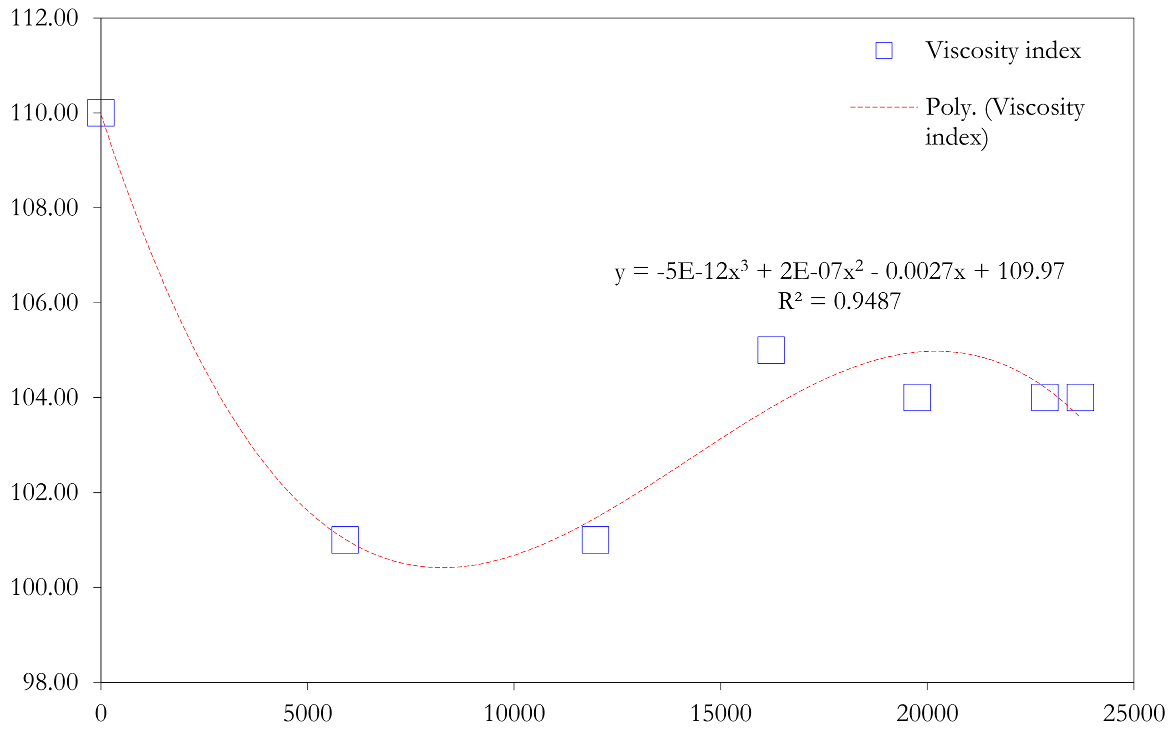

Figure 132. Data explanation of hydraulic cycles (x-axis) and viscosity index (y-axis)

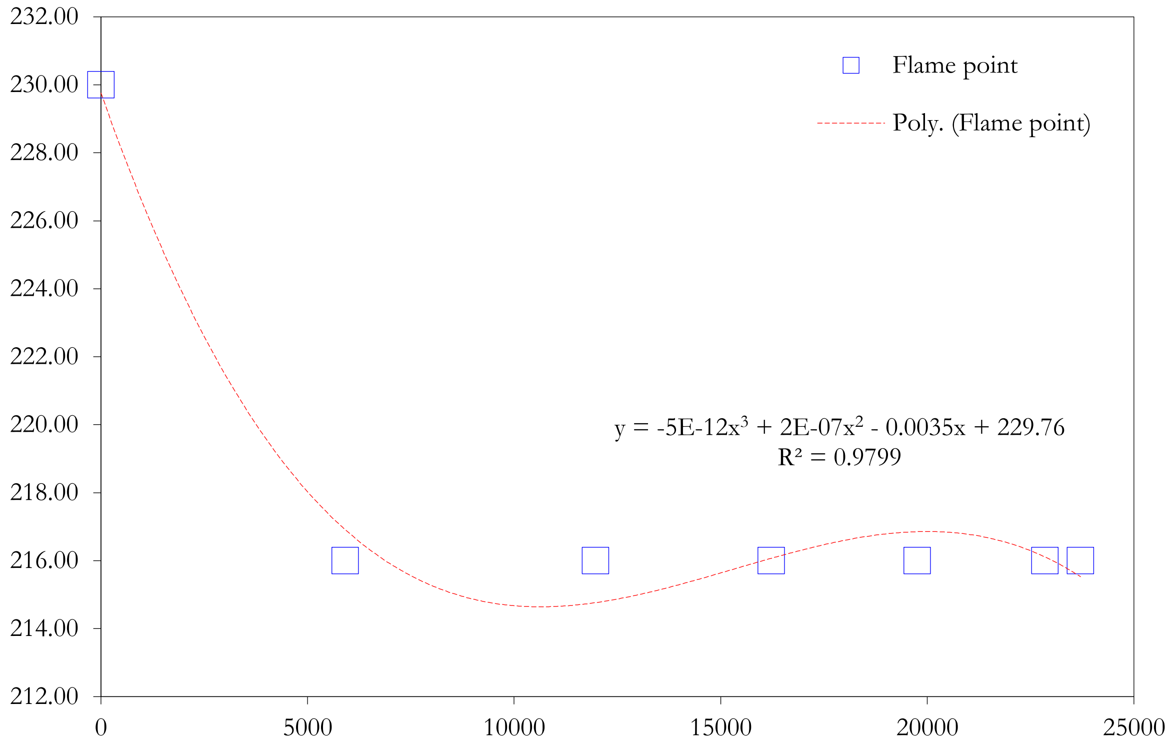

Figure 133. Data explanation of hydraulic cycles (x-axis) and flame point (y-axis)

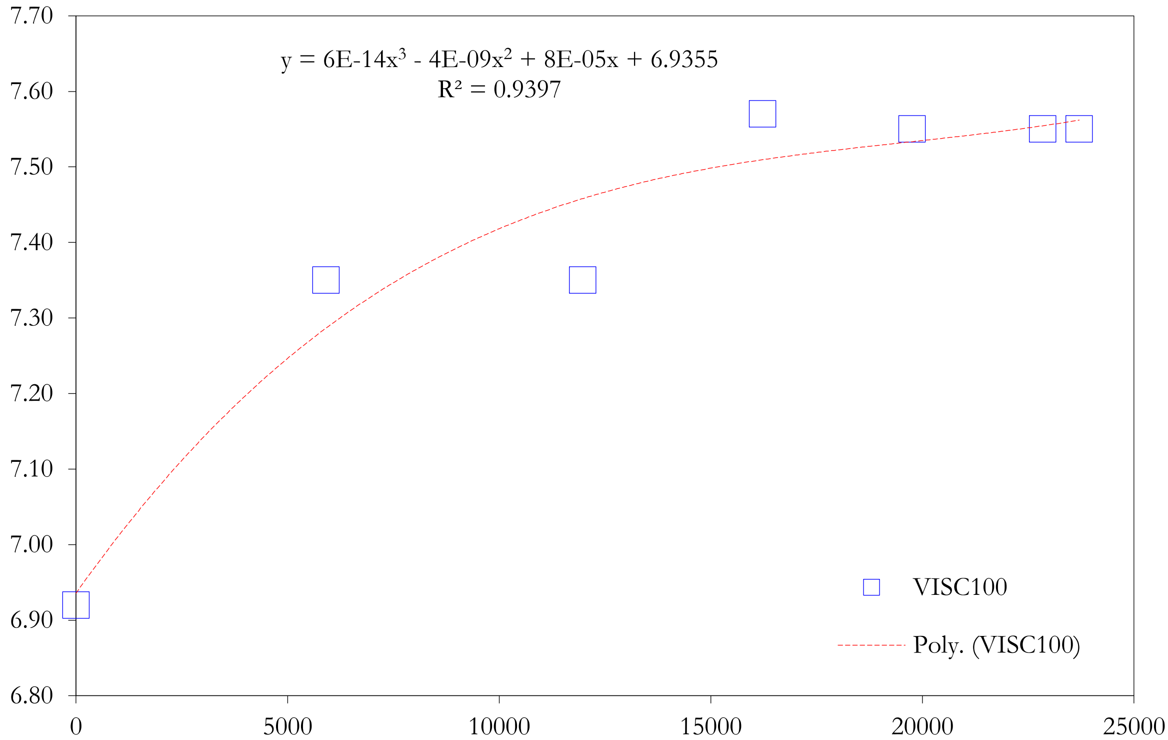

Figure 134. Data explanation of hydraulic cycles (x-axis) and viscosity 100°C (y-axis)

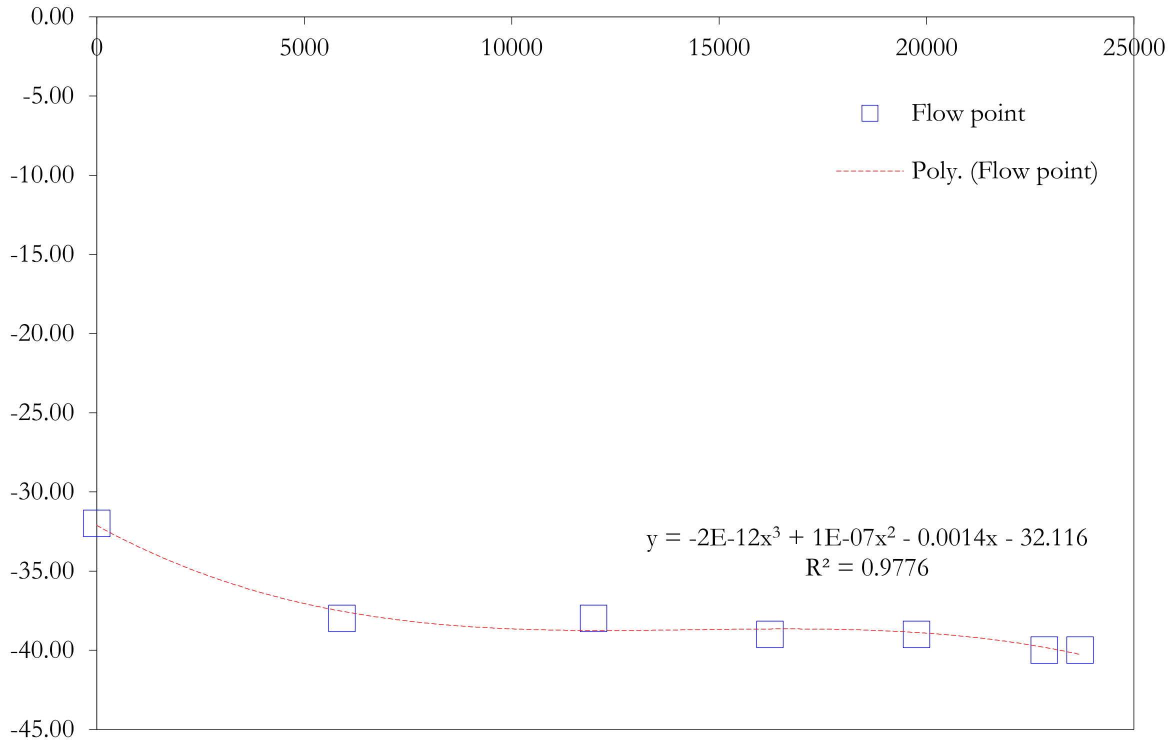

Figure 135. Data explanation of hydraulic cycles (x-axis) and flow point [ppm] (y-axis)

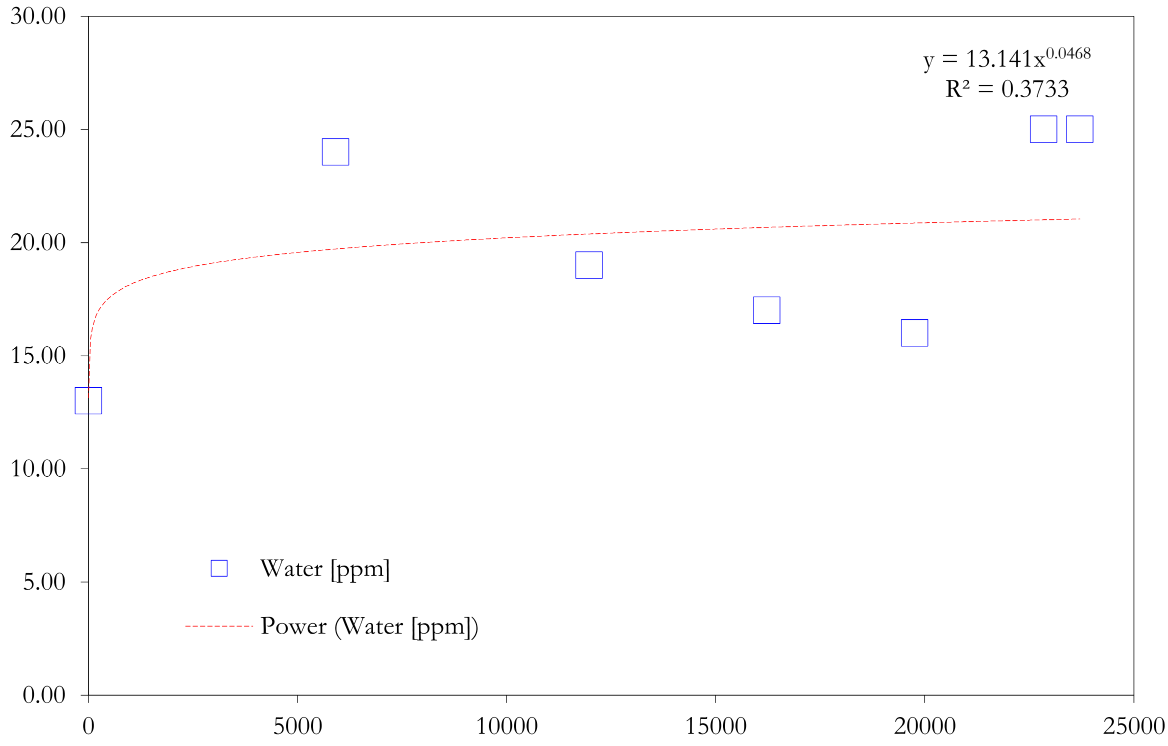

Figure 136. Data explanation of hydraulic cycles (x-axis) and Water [ppm] (y-axis)

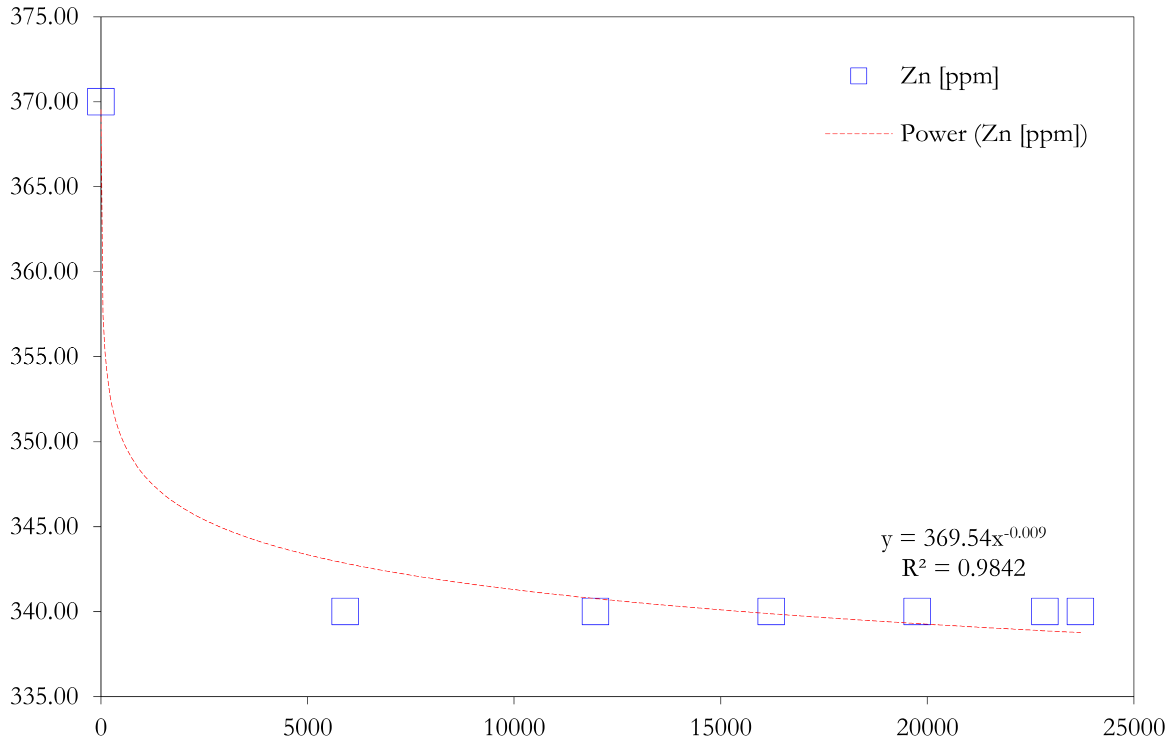

Figure 137. Data explanation of hydraulic cycles (x-axis) and Zn [ppm] (y-axis)

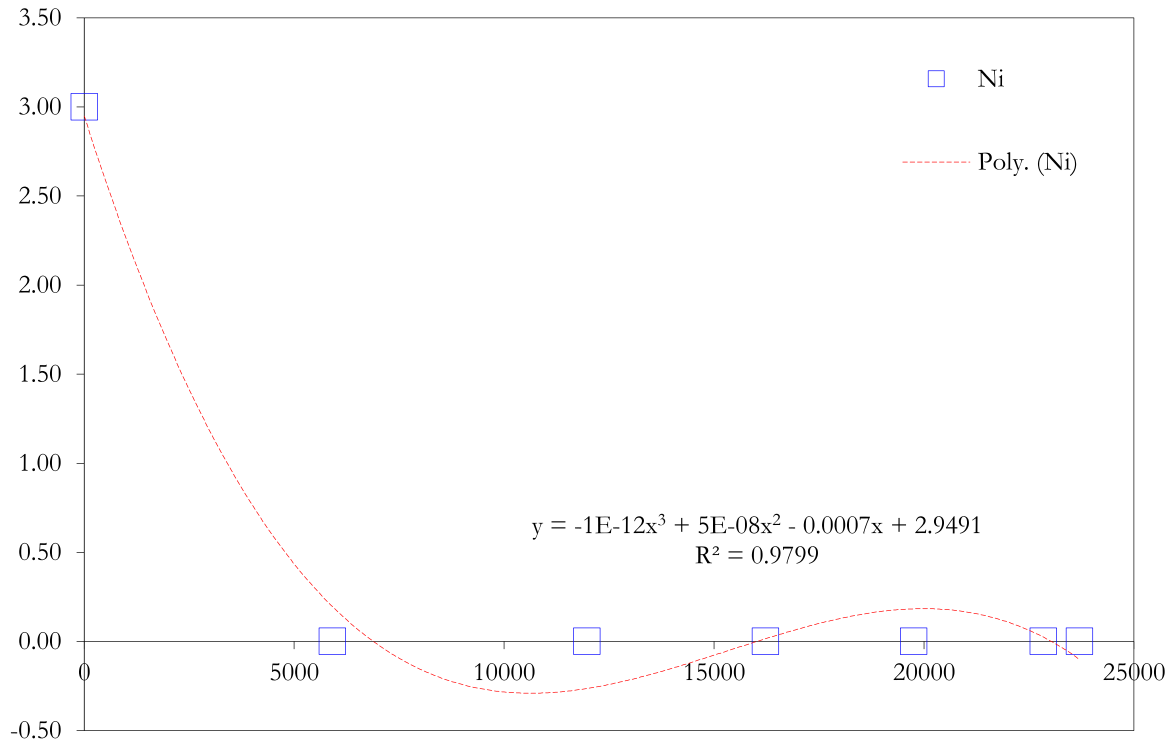

Figure 138. Data explanation of hydraulic cycles (x-axis) and Ni [ppm] (y-axis)

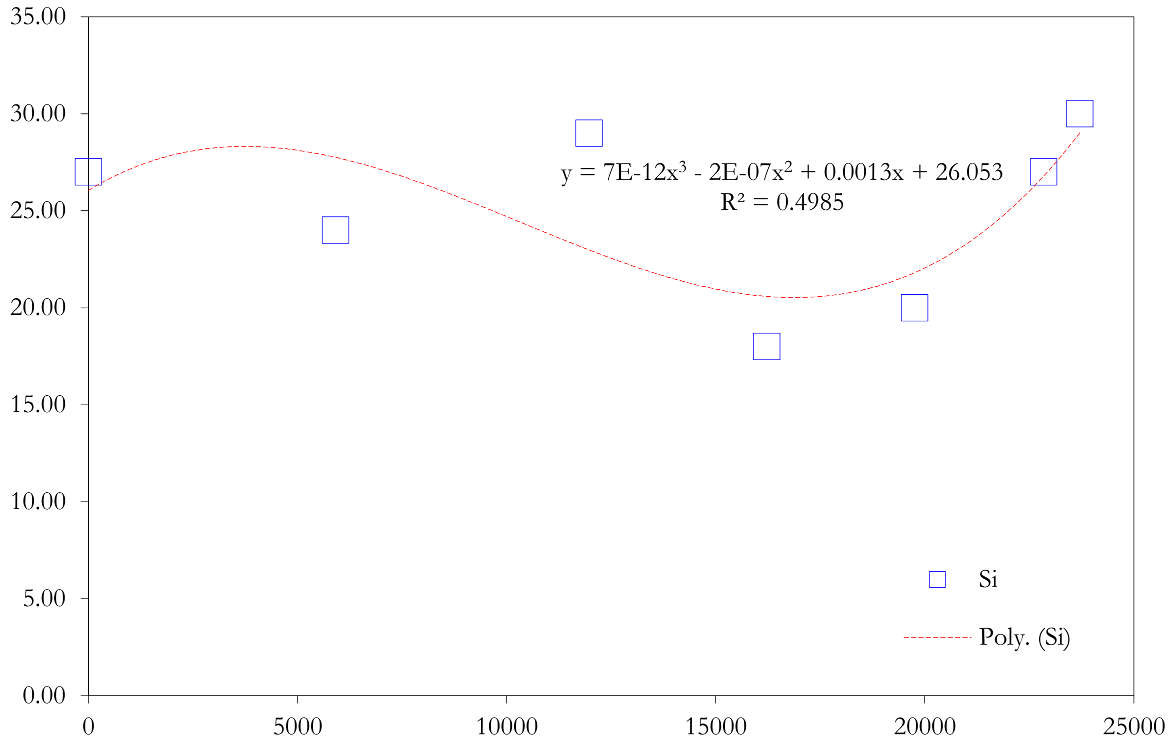

Figure 139. Data explanation of hydraulic cycles (x-axis) and Si [ppm] (y-axis)

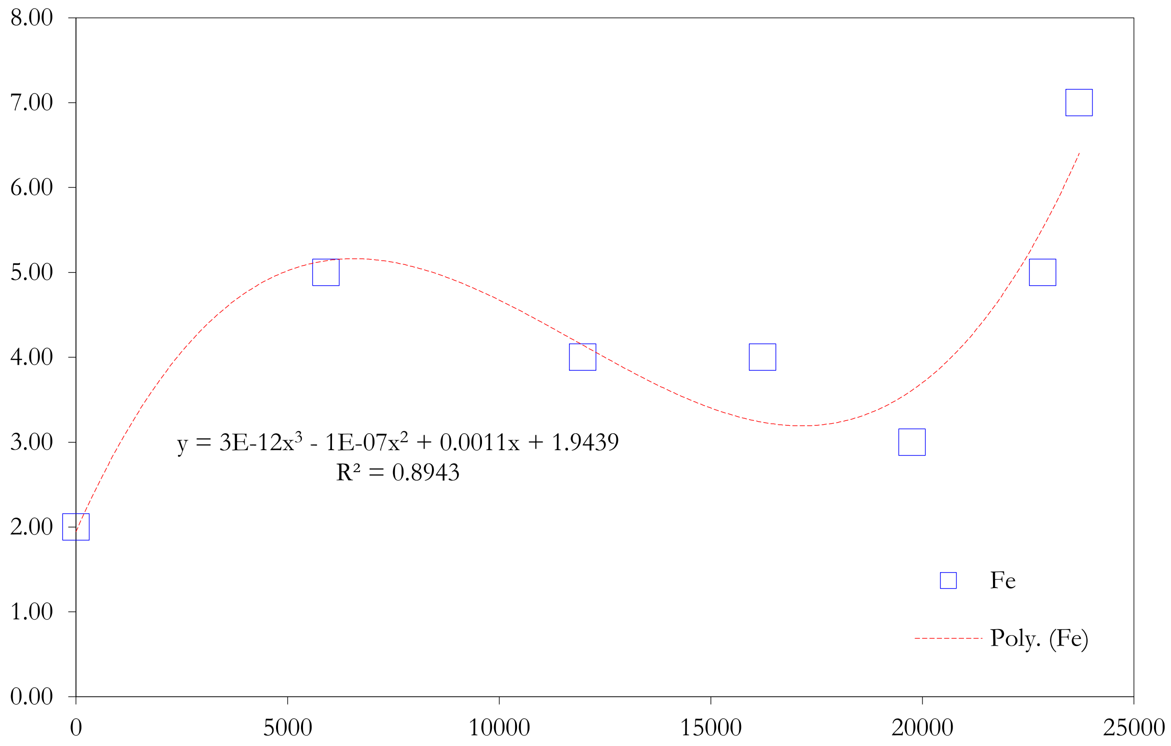

Figure 140. Data explanation of hydraulic cycles (x-axis) and Fe [ppm] (y-axis)

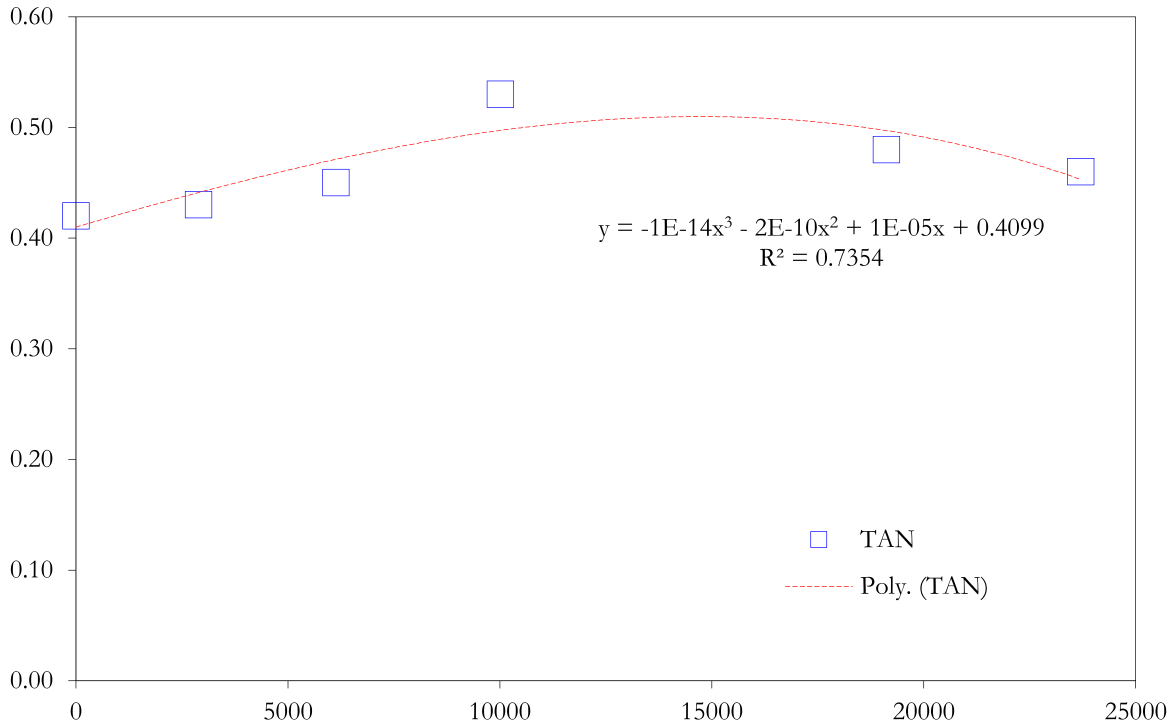

Figure 141. Data explanation of hydraulic cycles (x-axis) and TAN [mgKOH/g] (y-axis)

Appendix 13. Hydraulic power features before and after normalisation

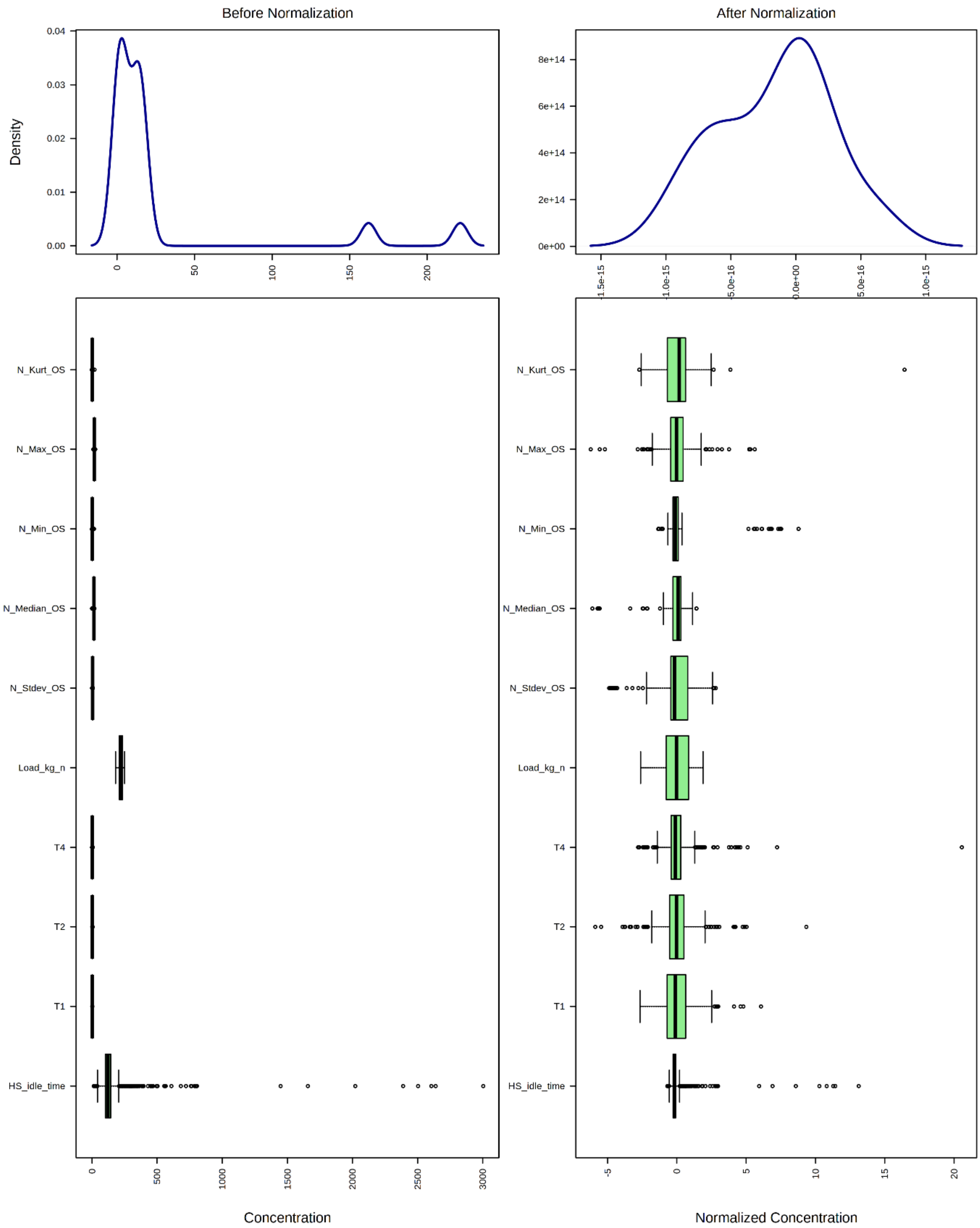

Figure 142. Opening saddle features after normalisation

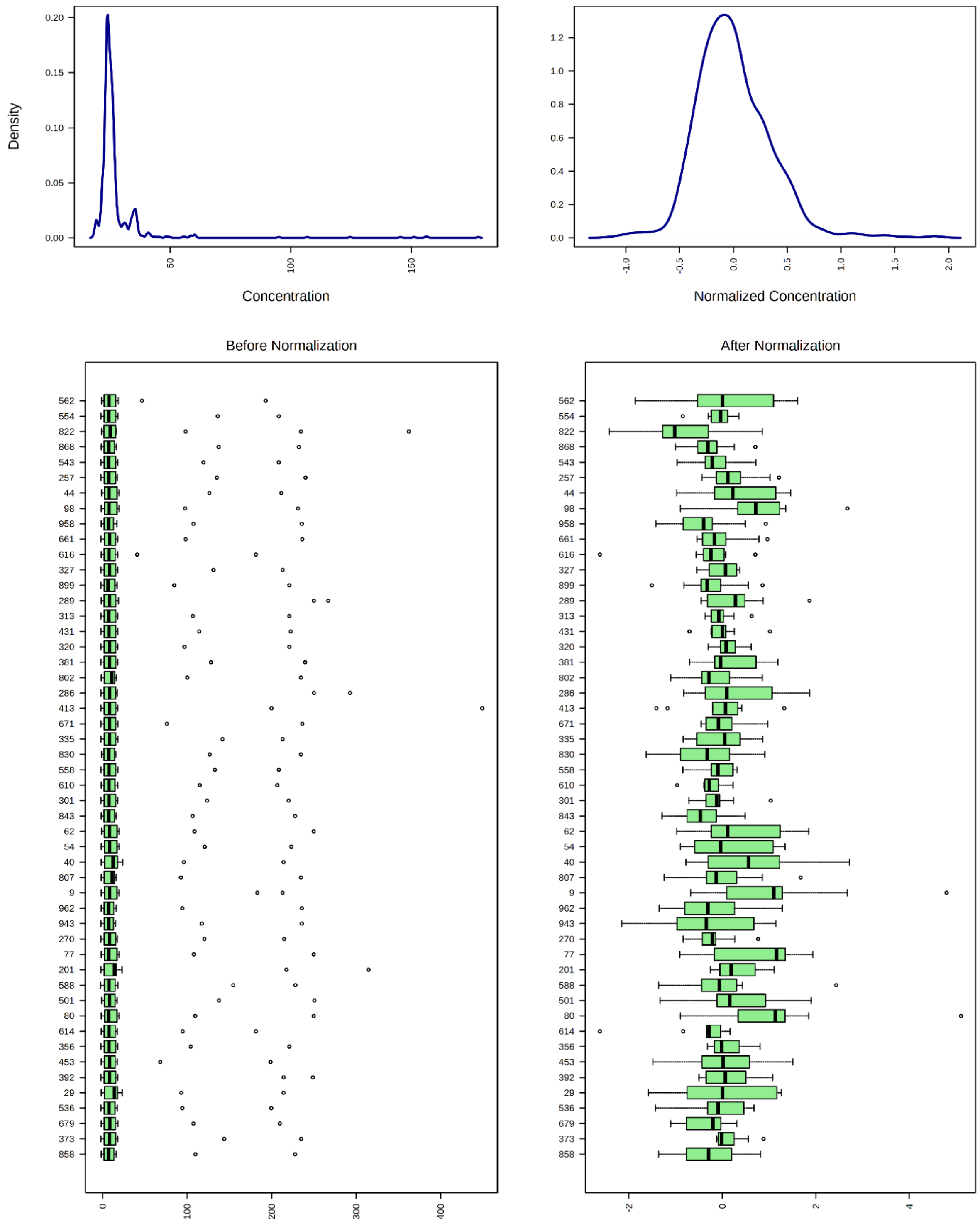

Figure 143. Opening saddle samples after feature normalisation

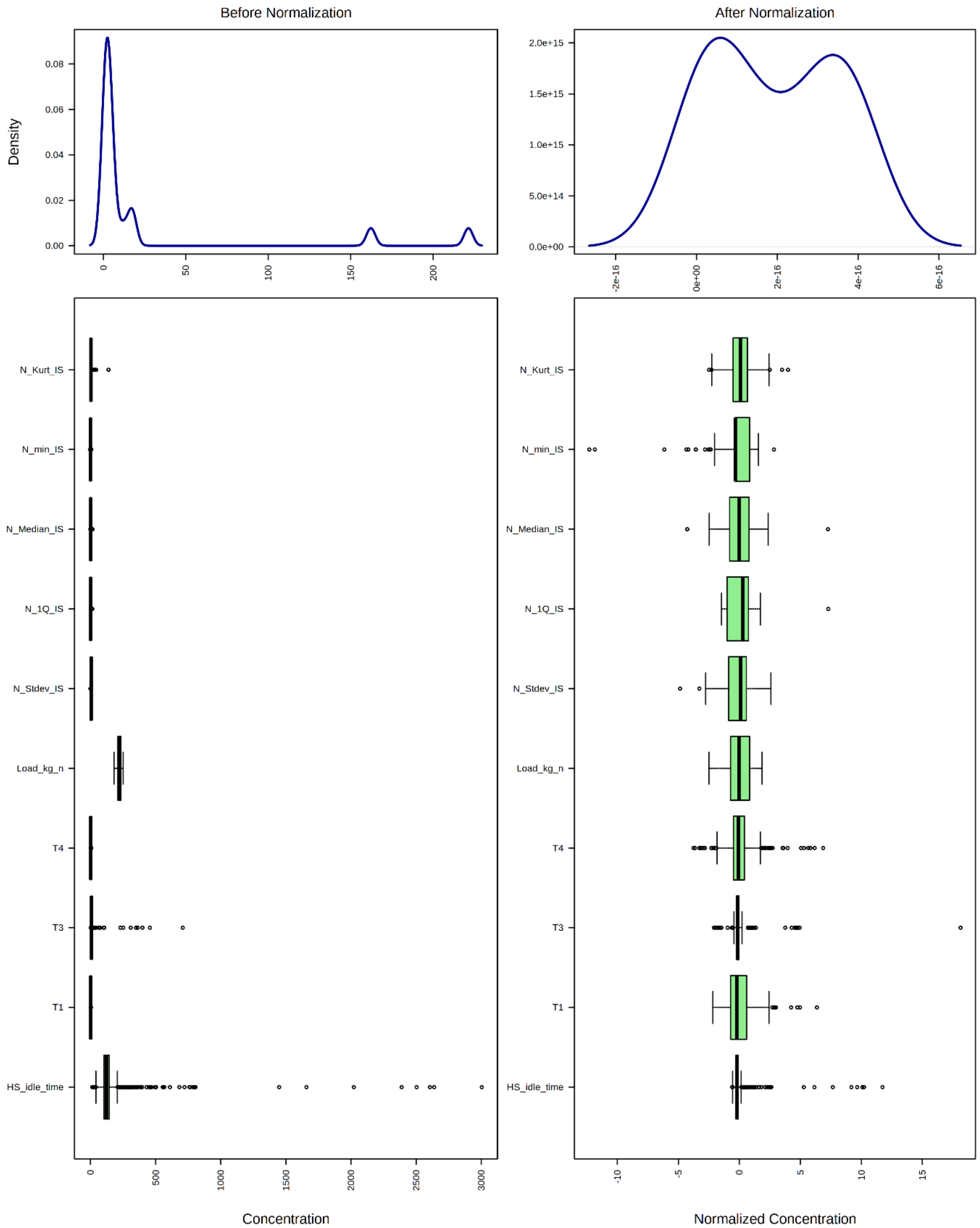

Figure 144. Idle saddle feature normalisation

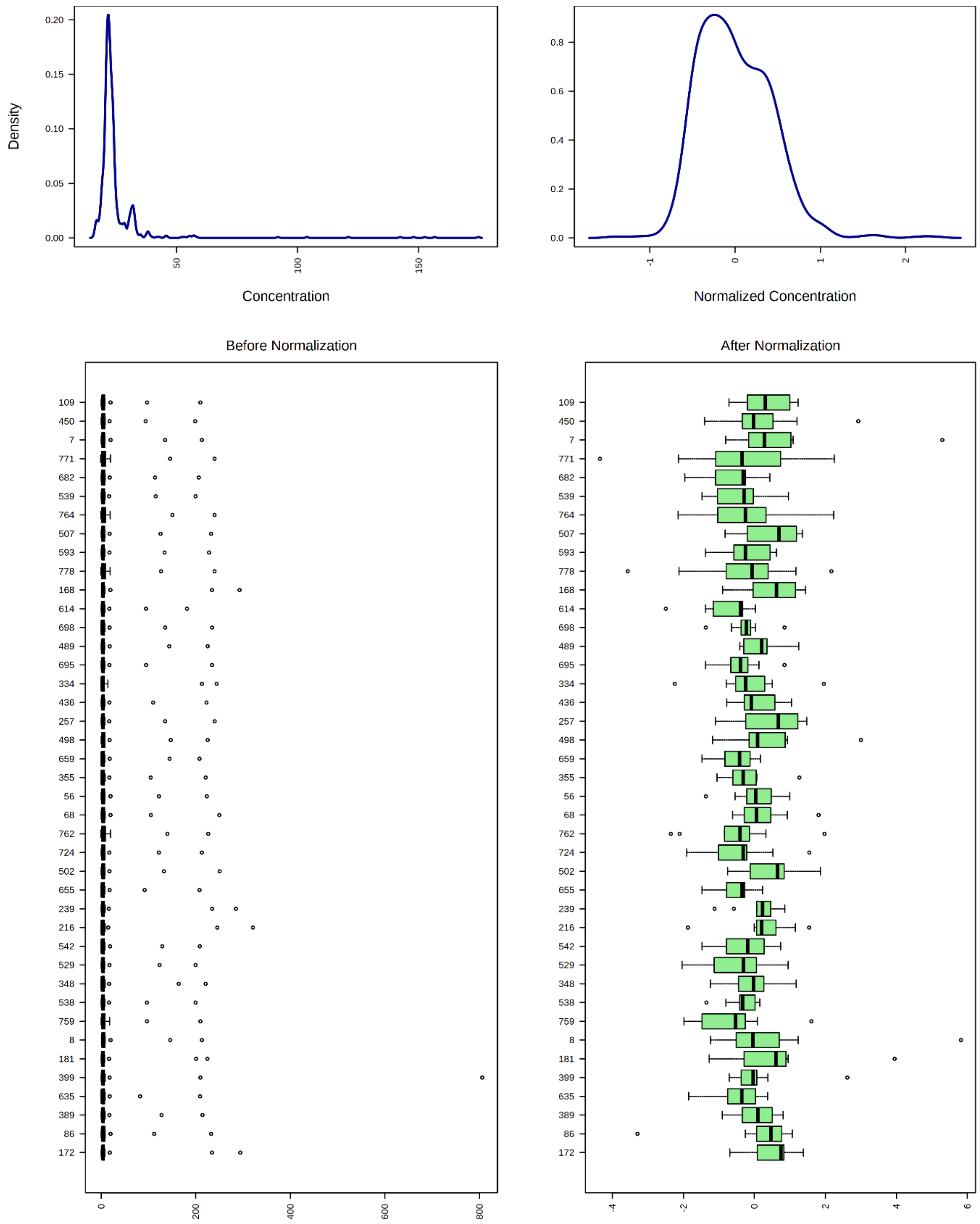

Figure 145. Idle saddle samples after feature normalisation

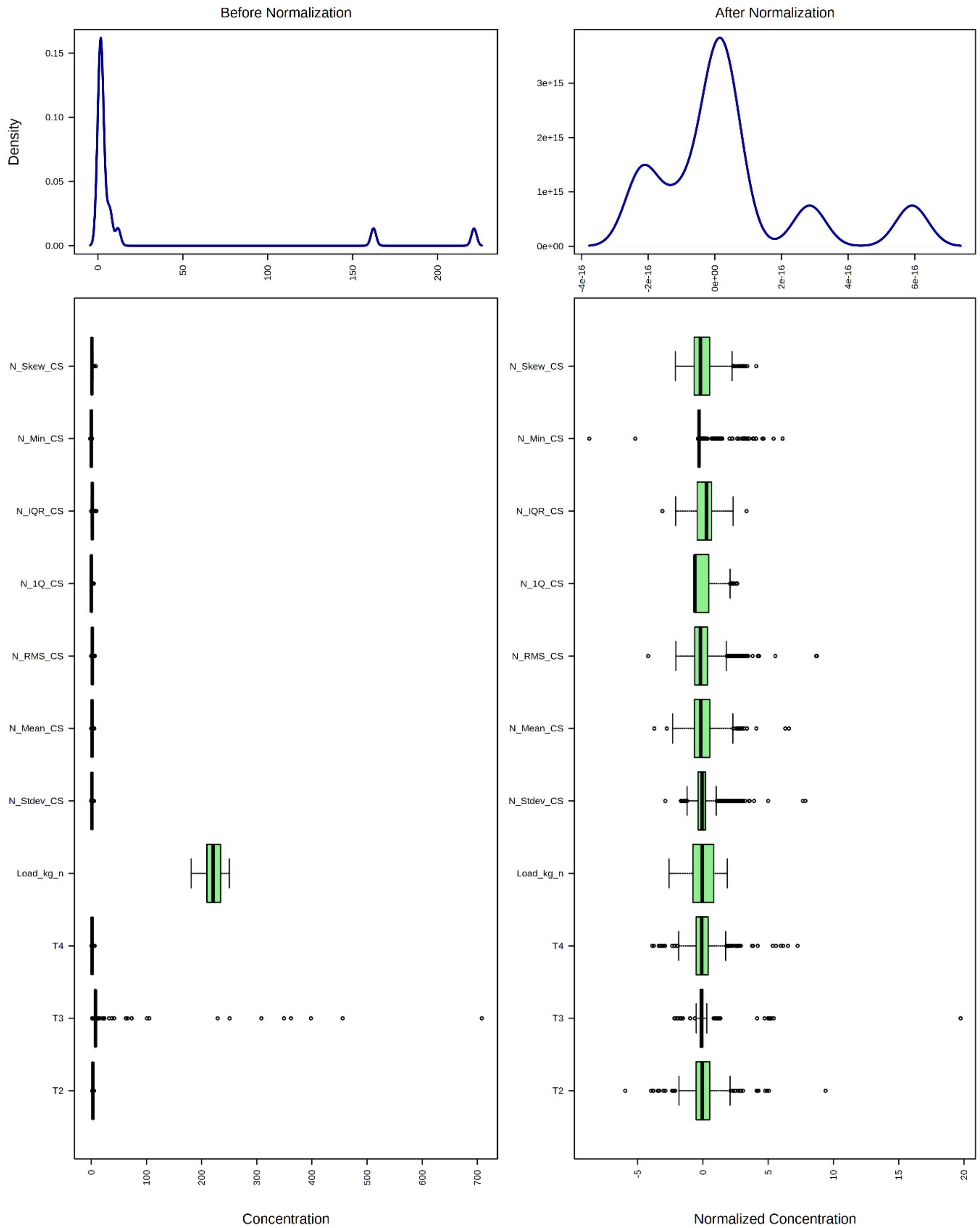

Figure 146. Closing saddle feature normalisation

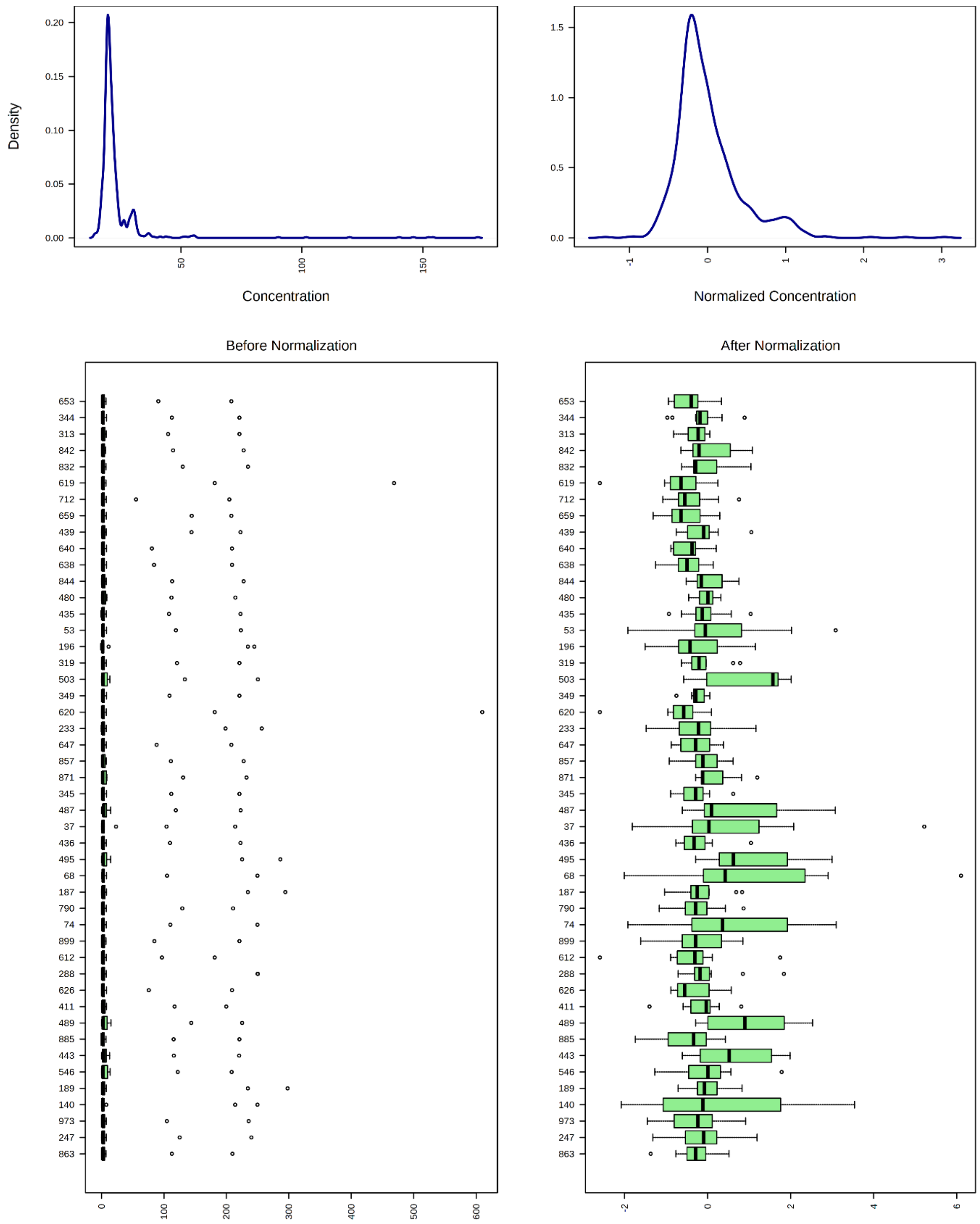

Figure 147. Closing saddle samples after feature normalisation

Appendix 14. JADbio[7] AutoML results of testing classification data using SVM

Conf.	Preprocess	DFA	HPM	ML	HPME	%PER	Time	Drop.
1	Removal const. Standardisation	Test-Budgeted Statistic. Equiv. Signature (SES) algorithm	maxK = 2, alpha= 0.05, budget = 3 * nvars	SVM	Kernel = 'Poly. Kernel', cost=1.0, gamma=1.0degree = 3	89.2%	00:00:01	false
2	Removal const. Standardisation	Test-Budgeted Statistic. Equiv. Signature (SES) algorithm	maxK = 2, alpha = 0.05, budget = 3 * nvars	SVM	kernel = 'Radial Basis Function Kernel', cost = 1.0, gamma = 1.0	91.1%	00:00:01	false
3	Removal const. Standardisation	Full Selector		SVM	kernel = 'Radial Basis Function Kernel', cost = 1.0, gamma = 1.0	93.8%	00:00:01	false
4	Removal const. Standardisation	Lasso feature selector	penalty 1.0	SVM	kernel = 'Radial Basis Function Kernel', cost = 1.0, gamma = 1.0	82.5%	00:00:01	false
5	Removal const. Standardisation	Lasso feature selector	penalty 1.0	SVM	kernel = Linear Kernel. Cost = 1.0	91.6%	00:00:01	false

NOTE: Explanation of preprocessing is done as according to all ML used. Different feature selection algorithm are represented by "DFA". HPM = Represents the hyperparameter changed in fitting the model for best performance; HPME = Represents the changes in hyperparameter made for fitting the model accordingly; %PER=Shows the performance of a model individually. TIME = Time to perform the model.

[7] https://app.jadbio.com/ Performance of a model was conducted by JADBio version 1.4.38 on an opening saddle dataset.

Овај Образац чини саставни део докторске дисертације, односно докторског уметничког пројекта који се брани на Универзитету у Новом Саду. Попуњен Образац укоричити иза текста докторске дисертације, односно докторског уметничког пројекта.

План третмана података

Назив пројекта/истраживања
СРП: „КОНЦЕПТ ФУНКЦИОНАЛНЕ ПРОДУКТИВНОСТИ ЗА МОДЕЛОВАЊЕ ПОУЗДАНОСТИ У ДОМЕНУ ОДРЖАВАЊА ЗАСНОВАНОМ НА ЕНЕРГИЈИ“ ЕНГ: „THE CONCEPT OF FUNCTIONAL-PRODUCTIVENESS FOR MODELLING RELIABILITY IN ENERGY-BASED MAINTENANCE DOMAIN“
Назив институције/институција у оквиру којих се спроводи истраживање
а) Факултет техничких наука Нови Сад б) Trelleborg, Ruma в)
Назив програма у оквиру ког се реализује истраживање
Истраживање је реализовано у сврху израде докторске дисертације.
1. Опис података
1.1 Врста студије *Укратко описати тип студије у оквиру које се подаци прикупљају* Тип студије подразумева примарни – оригинални научни допринос кроз експериментална запажања и обраду практичних примарних података из привредног сектора. Докторска теза такође подразумева и секундарни тип студије – преглед литературе и преглед пројеката у области индустријског одржавања кроз мета-анализу постојећих података. Доказивање главне хипотезе се спроводи кроз експериментална запажања индустријског процеса хидрауличког система. 1.2 Врсте података **а) квантитативни** б) квалитативни 1.3. Начин прикупљања података **<u>а) анкете, упитници, тестови</u>** б) клиничке процене, медицински записи, електронски здравствени записи в) генотипови: навести врсту ________________________________ г) административни подаци: навести врсту ________________________ д) узорци ткива: навести врсту___________________________________ ђ) снимци, фотографије: навести врсту______________________________ е) текст, навести врсту ____ ж) мапа, навести врсту ____

<u>з) остало:</u> <u>Експериментална запажања;</u>

1.3 Формат података, употребљене скале, количина података

1.3.1 Употребљени софтвер и формат датотеке:

<u>a) Excel фајл, датотека</u> <u>CSV</u>

b) SPSS фајл, датотека ___________________

c) PDF фајл, датотека ____________________

d) Текст фајл, датотека ___________________

e) JPG фајл, датотека ____________________

f) Остало, датотека _____________________

1.3.2. Број записа (код квантитативних података)

а) број варијабли: **n > 100; (али за експериментални део скраћено на око 14 промењљивих у 3 секвенцијална рада машине на којој је рађено испитивање)**

б) број мерења (испитаника, процена, снимака и сл.): **980 узорака по 3 секвенце**

1.3.3. Поновљена мерења

а) да

б) <u>НЕ</u>

Уколико је одговор да, одговорити на следећа питања:

а) временски размак између поновљених мера је ______________________________

б) варијабле које се више пута мере односе се на ________________________________

в) нове верзије фајлова који садрже поновљена мерења су именоване као ____________

Напомене: ____

Да ли формати и софтвер омогућавају дељење и дугорочну валидност података?

а) <u>ДА</u>

б) Не

Ако је одговор не, образложити ____

2. Прикупљање података

2.1 Методологија за прикупљање/генерисање података

2.1.1. У оквиру ког истраживачког нацрта су подаци прикупљени?

а) <u>експеримент, навести тип:</u> Аквизиција процесних података уз помоћ експеримената за мерење протока, притиска, нивоа контаминације, засићења водом, SCADA-е; лабораторијске анализе уља, итд. За сваки тип прикупљања и обраде података дат је јасно дефинисан протокол унутар докторске дисертације ради поштовања транспарентности и репродуцибилности.

б) корелационо истраживање, навести тип:

ц) анализа текста, навести тип ____

д) остало, навести шта ____

2.1.2 Навести врсте мерних инструмената или стандарде података специфичних за одређену научну дисциплину (ако постоје).

<u>Мерни инструменти:</u> Automatic Particle Counter CS1220 HYDAC (ISO 4406); AquaSensor HYDAC AS3000 (ISO 4406); SCADA Siemens систем; Wavelength Dispersive X-ray Fluorescence (WDXRF); Karl Fischer titracija (ASTM D3406-7); Kinematska viskoznost 40°C(ASTM D445-15a); Kinematska viskoznost na 100°C (ASTM D445-15a); Indeks viskoznosti (ASTM D2270-16); Kiselinski broj – Total Acid Number (TAN) (ASTM D664-11a); Sadržaj Zn (ASTM 4927-15).

2.2 Квалитет података и стандарди

2.2.1. Третман недостајућих података

а) Да ли матрица садржи недостајуће податке? Да **<u>НЕ</u>**

Ако је одговор да, одговорити на следећа питања:

а) Колики је број недостајућих података? Нема недостајућих података.

б) Да ли се кориснику матрице препоручује замена недостајућих података? Да Не

в) Ако је одговор да, навести сугестије за третман замене недостајућих података

2.2.2. На који начин је контролисан квалитет података? Описати

Аквизиција и обрада података мерним инструментима је извршена на основу датих стандарда за унапред напоменути мерни инструмент. Унос примарних података који подразумевају мета-анализу и систематски преглед литературе су прикупљени и обрађени према датим протоколима у докторату кроз инклузивном и ексклузивним критеријумима који се сматрају мером квалитета прикупљених података.

2.2.3. На који начин је извршена контрола уноса података у матрицу?

Прикупљање

3. Третман података и пратећа документација

3.1. Третман и чување података

3.1.1. Подаци ће бити депоновани у приватном репозиторијуму докторанта.

*3.1.2. **<u>URL адреса:</u>** https://trng-b2share.eudat.eu/records/a5fe55b906994289a30b0f6029fc11e6*

https://open.uns.ac.rs/handle/123456789/32444

3.1.3. DOI ____

3.1.4. Да ли ће подаци бити у отвореном приступу?

а) Да

*б) **<u>Да, али после ембарга који ће трајати до 01.09.2022</u>***

в) Не

Ако је одговор не, навести разлог:

3.1.5. Подаци неће бити депоновани у репозиторијум, али ће бити чувани.

„Сирови подаци“ ће бити депоновани у приватном репозиторијуму докторанта, док ће подаци обраде који су добијени (подаци спектрофотометријске анализе уља, физичко-хемијске анализе уља, подаци добијени на основу обраде, енергетски подаци, итд) анализом, бити приложени у докторату.

3.2 Метаподаци и документација података

3.2.1. Који стандард за метаподатке ће бити примењен?

3.2.1. Навести метаподатке на основу којих су подаци депоновани у репозиторијум.

____

Ако је потребно, навести методе које се користе за преузимање података, аналитичке и процедуралне информације, њихово кодирање, детаљне описе варијабли, записа итд.

____

____

3.3 Стратегија и стандарди за чување података

3.3.1. До ког периода ће подаци бити чувани у репозиторијуму? **Неограничено након ембарга**.

3.3.2. Да ли ће подаци бити депоновани под шифром? Да **НЕ**

3.3.3. Да ли ће шифра бити доступна одређеном кругу истраживача? Да **НЕ**

3.3.4. Да ли се подаци морају уклонити из отвореног приступа после извесног времена? Да **НЕ**

Образложити

____

4. Безбедност података и заштита поверљивих информација

Овај одељак МОРА бити попуњен ако ваши подаци укључују личне податке који се односе на учеснике у истраживању. За друга истраживања треба такође размотрити заштиту и сигурност података.

4.1 Формални стандарди за сигурност информација/података

Истраживачи који спроводе испитивања с људима морају да се придржавају Закона о заштити података о личности (*https://www.paragraf.rs/propisi/zakon_o_zastiti_podataka_o_licnosti.html*) и одговарајућег институционалног кодекса о академском интегритету.

4.1.2. Да ли је истраживање одобрено од стране етичке комисије? Да **НЕ**

Ако је одговор Да, навести датум и назив етичке комисије која је одобрила истраживање

____

4.1.2. Да ли подаци укључују личне податке учесника у истраживању? Да **НЕ**
ако је одговор да, наведите на који начин сте осигурали поверљивост и сигурност информација везаних за испитанике:

а) Подаци нису у отвореном приступу

б) Подаци су анонимизирани

ц) Остало, навести шта

____

____

5. Доступност података

5.1. Подаци ће бити

а) јавно доступни

<u>б) доступни само уском кругу истраживача у одређеној научној области</u>

ц) затворени

Ако су подаци доступни само уском кругу истраживача, навести под којим условима могу да их користе:

____

____

Ако су подаци доступни само уском кругу истраживача, навести на који начин могу приступити подацима: ____

____

5.4. Навести лиценцу под којом ће прикупљени подаци бити архивирани.

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6. Улоге и одговорност

6.1. Навести име и презиме и мејл адресу власника (аутора) података

Марко Орошњак, orosnjak@uns.ac.rs

6.2. Навести име и презиме и мејл адресу особе која одржава матрицу с подацима

Марко Орошњак, orosnjak@uns.ac.rs

6.3. Навести име и презиме и мејл адресу особе која омогућује приступ подацима другим истраживачима

Марко Орошњак, orosnjak@uns.ac.rs