19th IMEKO TC10 Conference
"MACRO meets NANO in Measurement for Diagnostics, Optimization and Control"
Delft, The Netherlands, September 21–22, 2023

WORK-IN-PROGRESS: RELIABILITY PREDICTION OF API CENTRIFUGAL PUMPS USING SURVIVAL ANALYSIS

Vila Forteza, M.[1,2], Galar Pascual, D. [1], Kumar, U. [1], Verma A.K.[3]

[1]Division of Operation and Maintenance Engineering, Luleå University of Technology, Luleå, Sweden, marc.vila.forteza@associated.ltu.se, diego.galar@ltu.se, uday.kumar@ltu.se
[2]Repsol, Petronor oil refinery, Muskiz, Bizkaia, Basque Country, Spain, mvilaf@repsol.com
[3]Faculty of Engineering and Natural Sciences, Western Norway University of Applied Sciences, Haugesund, Norway, ajitkumar.verma@hvl.no

Abstract –

In the Oil & Gas Industry, large fleets of centrifugal pumps are used for different services working in diverse process conditions. More specifically in oil refineries, they have many characteristics in common since they are centrifugal machines that handle liquids using the same operating principle and because their design is highly standardized by API 610/ISO 13709 std for centrifugal pumps and API 682 std for sealing systems. As well, operating units and refining processes are well known and do not differ much regardless of where they are installed.
Due to their criticality in the refining process, the reliability of these assets is of the utmost importance, being the MTBF (Mean Time Between Failures) one of the most used KPI (Key Performance Indicator) for evaluating it.
Considering the characteristics indicated above, the possibility of predicting the MTBF of centrifugal pumps based on historical failure data, design features and expected operating conditions with Cox Proportional Hazards Model (PHM) is suggested.

Keywords – **Centrifugal pumps, MTBF, API standard, Reliability prediction, Proportional Hazards Model, *Industry, Innovation, and Infrastructure.**

I. INTRODUCTION

Centrifugal pumps are characterised by the simplicity of their design, providing reasonable efficiencies, and covering a wide range of pressures, as well as being suitable for applications that require handling of liquid with reasonable amounts of solids. In the case of oil refineries, centrifugal pumps are often duplicated (to ensure full plant availability) and handles hazardous products, both in terms of their flammability and potential harmful effects on the environment and human health.
To ensure plant availability and due to the potential industrial accidents and high costs in lost profit that certain failures entail, industrial plants establish complete maintenance plans in their different modalities, as required, creating as well interdisciplinary groups that are continuously dedicated to the improvement and maximisation of the asset's reliability and integrity. Tools such as RCA, FMECA and others, as well as the most advanced failure detection and diagnosis techniques are widely implemented in this industry. [1]
In recent years, the development of Industry 4.0 in the Oil & Gas Industry (a review is available in [2] by Lu H. et al.) has led to the deployment of new field sensors and the development of algorithms that are used for fault diagnosis and Remaining Useful Life (RUL) determination to reduce failures and unwanted incidents. These algorithms use certain design features of the equipment, on-line operation data (available in the distributed control system) and vibration data (e.g. from new wireless sensors installed for this purpose).
To model failure progression, there are three basic ways: using symbols, data or mathematical equations based on physical principles. [3] See Fig. 1.

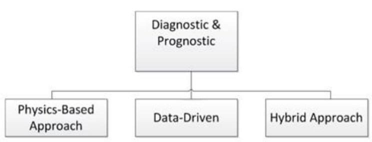

Fig. 1. Diagnosis y Prognosis Approaches [3]

The prognosis algorithms for machinery reliability have evolved in recent years, in [4] Soualhi A. et al. provide a survey of the implementation of prognostic methods for monitoring industrial systems, Mishra M. et al. in [3] summarise the various technologies that can be used for machinery diagnosis and prognosis in rotating equipment while McKee, K.K. et al. in [5] show a review of the state of the art in diagnosis and prognosis applied to centrifugal pumps. In the area of artificial intelligence, Aliyu, R. et al. in [6] develop a detailed study of the advances in AI-based system health management applied to pumps in the Oil & Gas industry.

The above-mentioned models are designed to detect specific failures and to determine the RUL of the equipment using data collected from on-line systems. The goal of these algorithms is to prevent failures either by modifying plant operating conditions or by anticipating maintenance tasks by diagnosing specific failures (for which vibration analysis techniques are needed) and predicting as accurately as possible the RUL. The resulting RUL is time-varying and depends on the health of the machine and its operating conditions thus allowing to make the most appropriate decisions according to the context. Examples of this type of algorithms applied to centrifugal pumps can be found in the literature, which seek to anticipate the most common failures or adverse working conditions in centrifugal pumps, e.g. bearing failures, cavitation, unbalance, misalignment, etc. The literature contains many examples of proposals for RUL prediction of components applied to centrifugal pumps, some of which can be found in [7-18].

On the other hand, Li X. et al. in [19] analyse the prognosis techniques of rotating equipment using system-level models, the purpose in this case is the prediction of the RUL at a system level. Examples of proposals in this direction, also applied to centrifugal pumps, can be found in [20-28]. Finally, a review of the statistical methods applied to the estimation of RUL of assets is presented in [29], which is a good guide to know the different existing methods and the literature published on this subject.

Despite the progress in determining the RUL of individual components as well as of the complete system (e.g. pumps), it is still difficult to determine the expected lifetime of a centrifugal pump both when it is commissioned or when it is started up after successive repairs during its lifetime. To know the maximum expected life of a pump can be useful for planning maintenance actions, calculating expected equipment operating costs, setting KPI's in line with the actual fleet or for improving the design of equipment that has a low MTBF (Mean Time Between Failures) and greater economic or safety impact. For this purpose, empirical MTBF data can currently be found in OREDA [30], books [31] or specialised journals, but to extrapolate these data to a specific industrial complex implies making a series of assumptions (design, operating conditions, data quality, etc.) that are difficult to assume if accurate results are required.

The main objectives of the research are to predict the expected MTBF of API centrifugal pumps installed in refineries and to determine how the design and operating variables affect the expected useful life of API centrifugal pumps. Maintenance would be better planned, indicators and targets could be set according to the installed fleet, and upgrades to the equipment could be easily addressed and justified, thus achieving higher reliability. For these purposes, the use of a Cox Proportional Hazards model is proposed, applied to an 8-year data set from a Spanish oil refinery.

II. COX PHM FOR MODELING RELABILITY

Cox PHM belongs to a set of methods called Survival Analysis. Such analysis comprises a number of statistical methods used to estimate time to event for a group of individuals, to compare time to event between two or more groups and to assess the relationship between the explanatory variables (covariates) and time to event. These methods can handle right censoring and assess time to a certain event and some examples of them are Kaplan-Meyer (descriptive), Logrank/Wilcoxon test (hypothesis test), exponential/Weibull (parametric) and Cox regression (semiparametric). An excellent self-learning text of survival analysis is [32] and it has good explanations and applied examples that can be used as a guide.

A. Brief description of Cox PHM Models

In early 70's David Cox first proposed the PHM to characterize the effect of different variables on the survival time or time to failure. First, these models were used in the biomedical research to predict the survival of individuals, but they are also used in reliability modelling of industrial equipment.

In a basic form, the Cox model for the failure rate h(t, Zt) in a certain time t, can be represented as follows (1):

$$h(t, Zt) = h_0(t)\Psi(\gamma Zt) \quad (1)$$

where $h_0(t)$ is the baseline hazard function, representing the failure rate of the equipment not affected by covariates, the link function $\Psi(\gamma Zt)$ is related to the covariate Zt value and the covariate coefficient γ weights the influence of the covariate on the failure rate. See Fig.2

PHM have the benefits that it is not necessary to assume a specific hazard rate functions and can effectively incorporate information on equipment service age and condition monitoring data, so it is suitable to estimate the probability of asset failure at any time in a given state and then evaluate the health state of the machine. [36]

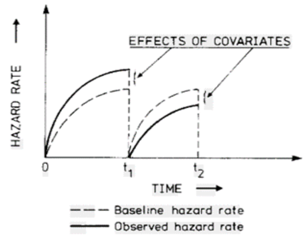

Fig. 2. Relation between the total hazard rate and the baseline hazard rate with covariates.[39]

On the other hand, the main assumptions of PHM are the following: first, Survival times of the individuals are independent; second, hazards are proportional, and the hazard ratio is constant over time; third, the covariates have a multiplicative effect on the baseline hazard rate.

References to the use of this type of models in reliability can be found in papers from the 90's [33] and more recent cases applied to prognosis and prediction of the failure rate of industrial assets in [34-38]. Finally, a summary of the research progress of the use of PHM in Prognosis is presented by Chaoqun D. et al in [36], including the advantages and current challenges to face in the future research of PHM applied to reliability.

II. CASE STUDY

A. Description the refinery production scheme

The refinery has two atmospheric distillation lines, which are based on two topping units, both have their associated product treatment units to meet the required standards. These units are the kerosene, naphtha and diesel desulphurisation units. The hydrogen required in these units is produced in two steam reforming plants, which are also installed in the same area.

The production scheme is completed with two deep conversion areas, the first is the conversion area comprising the vacuum distillation unit, fed by the residue from the topping units. In this area, in addition to the product treatment units adapted to the characteristics of the cracked fractions, there is also an FCC (Fluid Catalytic Cracking) unit which transforms the cracked products extracted in the vacuum unit into products that are suitable to be processed in the desulphurisation units and converted into final products, mainly diesel, gasoline and LPG.

There is also a more recent area, designed to reduce fuel oil production, which performs a deeper conversion through the required technology to convert the residue from the vacuum unit into valuable products, mainly naphtha and diesel. Again, to convert these products into final products for sale, there are naphtha and diesel desulphurisation plants. Each of these production areas, has units that reduce gaseous and liquid emissions, these are the sulphur plants and the acid and ammonia water treatment plants to complete the adaptation of products.

Finally, the refinery has many tanks and spheres and a maritime dock. In the first area, crude oil, intermediate products, and final products are stored and transferred (by pumps) both inside and outside the refinery. In the second area, the maritime dock, the raw products are received, and the final products obtained from their transformation in the industrial plant are shipped.

B. Dataset of centrifugal pumps

The refinery being studied has a fleet of 3,200 rotating machinery items, including air coolers, centrifugal and reciprocating compressors, centrifugal fans, both centrifugal and positive displacement pumps, steam turbines, among others (see Fig. 3). Up to 1,194 items are centrifugal process pumps, which represents a 38% of the rotating equipment of the plant.

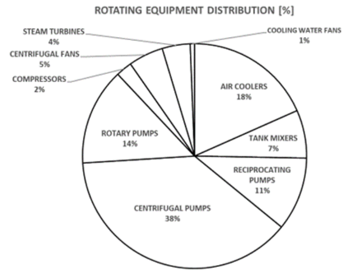

Fig. 3. Distribution [%] of rotating equipment in the refinery.

The atmospheric distillation area has the highest percentage of centrifugal process pumps in the refinery, while the tanks and marine terminal area has the fewest. Table 1 shows the distribution of centrifugal pumps as a percentage of the plant and of the dataset used (consisting in 675 centrifugal pumps). We selected a sample of 675 centrifugal pumps of different designs and operating conditions in such a way that it would be representative.

The different proportion of pumps corresponding to tanks and dock in the dataset with respect to the global refinery is because in this area there is a significant amount of equipment that works discontinuously or for which there is not enough vibration data available due to the few working hours accounted during the year.

Table 1. Distribution of centrifugal pumps by production area.

	Dataset		Refinery	
	% pumps	# pumps	% pumps	# pumps
Atmospheric distillation area	44.8%	303	41.3%	503
Conversion area	35.8%	241	26.3%	320
Fuel reduction area	12.2%	82	10.8%	132
Tanks and dock	7.3%	49	21.6%	263

C. Potential predictor variables

The dataset includes age, design standards (API), global vibration value and operating conditions as well as other hydraulic parameters which, according to the available literature [30] and the expertise of plant technical staff, can most affect the service life of these assets. See Fig. 4.

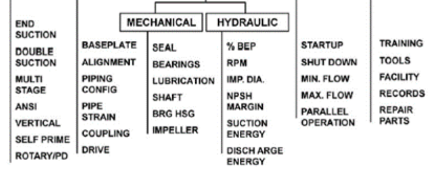

Fig. 4. Factors affecting reliability of centrifugal pumps [30].

The output variable is the number of failures recorded in 8 years (from 2014 to 2022) which repair required the shutdown of the pump. On the other hand, a total of 22 variables are considered as potential predictors of the failure rate of the centrifugal pumps, which are divided into 5 groups (operating conditions, hydraulics, mechanical, sealing and age). It should be kept in mind that the operating conditions of the pump (which may change over time) are not being specified for each failure, since this study is intended to assess the potential maximum useful life of the pumps considering their design characteristics and expected operating conditions. See Table 2.

Table 2. Potential predictor variables for MTBF.

OPERATING CONDITIONS	HYDRAULICS	MECHANICAL	SEALING	AGE
Fluid type	Double suction	rpm	Seal arrgt.	API 610 ed
ISO 10816-7 vibration zone	Tip speed	Power	Seal type	
Bottom pump	Diameter ratio	Bearing type	API 682 Plan	
Flow ratio	Efficiency	Lubrication type	# Seals	
NPSH margin	Nss			
Relative density				
Dynamic viscosity				
Vapour pressure				

To better understand what the variables used refer to and why they have been selected, a brief description of each of them is given below, indicating as well if they are of the categorical (CA) or continuous (CO) type.

- Fluid type (CA): Categorised according to the material selection guide Annex G - API 610 12th.
- ISO 10816-7 Vibration Zone (CA): Category 1 equipment (ISO 10816-7) is considered, and the vibration severity of each machine is assessed as A, B, C and D according to the standard.
- Bottom tower pump (CA): This indicates whether the pump handles the product from the bottom of a tower or not. This service usually presents problems of filter clogging and soot.
- Flow ratio (CO): The operation of centrifugal pumps at flows far from the BEP (Best efficiency point) reduces the useful life of the equipment, so the normal Flow vs Flow BEP ratio is used to assess how the flow affects the life of the pump.
- NPSH margin (CO): The suction conditions are particularly important, to avoid cavitation problems. The difference between $NPSH_d$ and $NPSH_r$ at the rated operating point of the pump is considered.
- Relative density (CO): The density of the fluid can have a certain influence on the pump behaviour, e.g., working pressure, power consumption, vibrations, or mechanical seal. The density relative to water is used.
- Dynamic viscosity (CO): The dynamic viscosity of the fluid is considered because it can affect differential head, torque and internal frictions in impeller and pump casing.
- Vapour pressure (CO): Evaluated with the NPSHd, it can give an idea of the possibility of the fluid vaporising at the pump suction and therefore cavitation or performance problems.
- Double suction (CA): Double suction pumps have special hydraulic and operating characteristics vs single suction impellers.
- Tip speed (CO): The speed at which the fluid leaves the impeller tip is important when assessing possible internal erosion if solids are present in the fluid stream.
- Diameter ratio (CO): The ratio of installed impeller diameter vs. maximum allowable impeller diameter for the installed casing is used, as hydraulic problems can arise if the gap between them is narrow.
- Efficiency (CO): There are many factors that influence the efficiency of pumps, noise, internal recirculation, vibrations, mechanical and hydraulic friction, etc. Some of these can affect the useful life of the equipment.
- Nss (CO): Suction specific speed is a dimensionless indicator that relates the geometry of the impeller at suction and certain characteristics at suction, such as rpm, $NPSH_r$ and flow rate.
- RPM (CA): The rotational speed can influence the reliability of centrifugal pumps as it can affect the service life of bearings and mechanical seals or abrasive wear. Three categories of speed are identified: low, medium, and high speed.
- Power (CO): Power has been considered because it may be reasonable to think that certain mechanical problems (e.g. unbalance, misalignment, etc.) may evolve differently depending on the working power of the driver.
- Bearing type (CA): Plain bearing and roller bearing are considered because they are an important cause of failures in rotating equipment and specifically also in centrifugal pumps.
- Lubrication type (CA): Various lubrication systems have been categorised: oil mist, oil ring, forced lubrication.
- Seal arrangement (CA): Cartridge seal, component seal and seals for high-speed pumps are considered.
- Seal type (CA): Dual seals and single seals.
- API std 682 plan (CA): A difference is made between pressurised dual seals (e.g. API Plan 53A, 54, etc.) and non-pressurised dual or single seals (e.g. API Plan 52, 12, etc.).
- # Seals (CA): The number of mechanical seals of the pump is considered, overhung pump (1 seal) or a double supported pump (2 seals).
- API 610 std edition (CA): To assess the age and the improvements made to each of the centrifugal pumps we use the edition of API 610 std under which they have been designed. The dataset includes pumps manufactured according to the 4th edition (year

1965) up to the 11th (year 2010).

III. WORK-IN-PROGRESS COX PHM MODEL

Before addressing the development of models to achieve the stated goals, a detailed analysis of the nature of the data should be carried out and an assessment should be made of if the available methods have been successfully used for similar cases. The following considerations should also be considered:

- There are pumps that did not fail during the survey, so the dataset has some 0's as outcome.
- The number of recorded failures is a discrete and limited variable (from 0 to 35), so that several assets have the same outcome and therefore the same failure rate and MTBF.
- For the further development of the models, it is important to determine whether it is assumed that after a repair the asset is in 'good as new' condition.
- The predictor variables are time invariant (expected operating conditions and hydraulic and mechanical design). On the other hand, the overall vibration is an average data for the time frame considered.

We are currently in the phase of basic statistical analysis and data cleaning and at the same time we are checking if the Proportional Hazard Model (PHM) is suitable for meeting the proposed objectives with the available dataset. The results of the developed PHM models will be compared to determine which one offers better results for the prediction of the expected MTBF in centrifugal pumps, as well as in the determination of those covariates that have a greater impact. Finally, these results will be contrasted with reliability data from another similar refinery to check the accuracy of the models.

IV. CONCLUSIONS AND OUTLOOK

Centrifugal pumps are widely used in industry because of their versatility and simplicity of design. In oil refineries, centrifugal pumps account for more than 35% of the rotating equipment fleet and handle highly hazardous products. It is therefore essential to maximise their reliability, as any failure of these assets could result in an accident. For this reason, as well as the high production loss caused by a plant shutdown, maintenance and inspection schedules in this industry are strict to optimise the pump's reliability. In this paper we propose to develop a Cox Proportional Hazards model, applied to API centrifugal pumps, to predict the maximum expected time between failures of these assets as a function of variables of interest (covariates). An accurate prediction of this indicator would help to set other KPI's and targets according to the characteristics of the fleet, so that maintenance activities could be better planned. The PHM model would also be used to determine how these covariates affect the expected useful life of API centrifugal pumps, thus helping to increase their reliability and reduce the risk of accidents and operating costs.

This type of model is currently used for predicting industrial equipment. It incorporates relevant design characteristics, operating time, and on-line data to predict the health status of the machine at any given time. In the present case, their application is proposed on a dataset that includes pump design variables (hydraulic and mechanical) as well as those related to the API 610 standard for centrifugal process pumps and 682 for sealing systems.

A future area of research for this project is the integration of on-line operating data from distributed control systems (DCS) and vibration signals to change the paradigm from statistically based to real condition-based prediction of the assets' useful life.

REFERENCES

[1] **Vila Forteza, M., Galar, D., Lin, J., Liyanage, J. P.** (2022): New paradigms in Maintenance, operation, and health management of rotating machinery large fleets. The effect of Industry 4.0. *18th International Conference on Condition Monitoring and Asset Management* (CM2022), 311–321.

[2] **Lu, H., Guo, L., Azimi, M., Huang, K.** (2019): Oil and Gas 4.0 era: A systematic review and outlook. *Computers in Industry* (Vol. 111, pp. 68–90). Elsevier. https://doi.org/10.1016/j.compind.2019.06.007.

[3] **Mishra, M., Saari, J., Galar, D., Leturiondo, U., Luleå tekniska universitet. Institutionen för samhällsbyggnad och naturresurser.** (2014): Hybrid Models for Rotating Machinery Diagnosis and Prognosis Estimation of Remaining Useful Life. *Luleå tekniska universitet.*

[4] **Soualhi, A., Lamraoui, M., Elyousfi, B., Razik, H.** (2022): PHM SURVEY: Implementation of Prognostic Methods for Monitoring Industrial Systems. Energies. 2022; 15(19):6909. https://doi.org/10.3390/en15196909.

[5] **McKee, K.K., Forbes, G.L., Mazhar, I., Entwistle, R., Howard, I.** (2014): A Review of Machinery Diagnostics and Prognostics Implemented on a Centrifugal Pump. In: Lee, J., Ni, J., Sarangapani, J., Mathew, J. (eds) *Engineering Asset Management 2011. Lecture Notes in Mechanical Engineering*.Springer,London. https://doi.org/10.1007/978-1-4471-4993-4_52.

[6] **Aliyu, R., Mokhtar, A. A., Hussin, H.** (2022): Prognostic Health Management of Pumps Using Artificial Intelligence in the Oil and Gas Sector: A Review. *Applied Sciences*, *12*(22), 11691. https://doi.org/10.3390/app122211691.

[7] **Vila Forteza, M., Jimenez Cortadi, A., Diez Olivan, A., Seneviratne, D., Galar Pascual, D. (2023)**: Advanced Prognostics for a Centrifugal Fan and Multistage Centrifugal Pump Using a Hybrid Model. 10.1007/978-981-99-1988-8_12.

[8] **Adraoui, I. E., Gziri, H., & Mousrij, A.** (2020): Prognosis of a degradable hydraulic system: Application on a centrifugal pump. *International Journal of Prognostics and Health Management*, 11(2), 1–11.

[9] **Cubillo, A., Perinpanayagam, S., Esperon Miguez, M.** (2016): A review of physics-based models in prognostics: Application to gears and bearings of rotating machinery. *Advances in Mechanical Engineering.* 8. 10.1177/1687814016664660.

[10] **Zhang, S., Hodkiewicz, M., Ma, L., Mathew, J.** (2006): Machinery Condition Prognosis Using Multivariate Analysis. In: Mathew, J., Kennedy, J., Ma, L., Tan, A., Anderson, D. (eds) *Engineering Asset Management.* Springer, London. https://doi.org/10.1007/978-1-84628-814-2_89.

[11] **Anil Kumar, C.P. Gandhi, Yuqing Zhou, Rajesh Kumar, Jiawei Xiang.** (2020): Improved deep convolution neural network (CNN) for the identification of defects in the centrifugal pump using acoustic images, *Applied Acoustics, Volume* 167, 2020, 107399, ISSN 0003-682X, https://doi.org/10.1016/j.apacoust.2020.107399.

[12] **Souza, R., Sperandio N., Erick G., Miranda, U., Silva, W., Lepikson, H.** (2020): Deep learning for diagnosis and classification of faults in industrial rotating machinery. *Computers & Industrial Engineering.* 153. 107060. 10.1016/j.cie.2020.107060.

[13] **Yu, R., Li, X., Tao, M., Ke, Z.** (2016): Fault Diagnosis of Feedwater Pump in Nuclear Power Plants Using Parameter-Optimized Support Vector Machine. V001T03A013. 10.1115/ICONE24-60334.

[14] **Zurita Millan, D., Delgado-Prieto, M., Saucedo-Dorantes, J., Cariño-Corrales, J., Osornio-Rios, R., Ortega, J., Romero-Troncoso, R.** (2016): Vibration Signal Forecasting on Rotating Machinery by means of Signal Decomposition and Neurofuzzy Modeling. Shock and Vibration. 2016. 1-13. 10.1155/2016/2683269.

[15] **Fouladirad, M., Belhaj Salem, M., Deloux, E.** (2022): Variance Gamma process as degradation model for prognosis and imperfect maintenance of centrifugal pumps. *Reliability Engineering & System Safety.* 223. 108417. 10.1016/j.ress.2022.108417.

[16] **Zhao, L., Wang, X.** (2018): A Deep Feature Optimization Fusion Method for Extracting Bearing Degradation Features. *IEEE Access.* PP. 1-1. 10.1109/ACCESS.2018.2824352.

[17] **Zhang, Y., Zhou, T., Huang, X., Longchao, C., Zhou, Q.** (2020): Fault diagnosis of rotating machinery based on recurrent neural networks. *Measurement.* 171. 10.1016/j.measurement.2020.108774.

[18] **Cao, S., Hu, Z., Luo, X., Wang, H.** (2020): Research on fault diagnosis technology of centrifugal pump blade crack based on PCA and GMM. *Measurement.* 173. 108558. 10.1016/j.measurement.2020.108558.

[19] **Li, X., Duan, F., Mba, D., Bennett, I.** (2017): Rotating machine prognostics using system-level models. *Lecture Notes in Mechanical Engineering*, 0(9783319622736), 123–141. https://doi.org/10.1007/978-3-319-62274-3_11.

[20] **Wang, J., Zhang, L., Zheng, Y., Wang, K.** (2019): Adaptive prognosis of centrifugal pump under variable operating conditions. *Mechanical Systems and Signal Processing*. 131. 576-591. 10.1016/j.ymssp.2019.06.008.

[21] **Zhang, Q., Hua, C., Xu, G.** (2014): A mixture Weibull proportional hazard model for mechanical system failure prediction utilising lifetime and monitoring data. *Mechanical Systems and Signal Processing.* 43. 103–112. 10.1016/j.ymssp.2013.10.013.

[22] **Hu, J., Tse, P.** (2013): A Relevance Vector Machine-Based Approach with Application to Oil Sand Pump Prognostics. *Sensors (Basel, Switzerland).* 13. 12663-86. 10.3390/s130912663.

[23] **Mosallam, A., Medjaher, K., Zerhouni, N.** (2014): Data-driven prognostic method based on Bayesian approaches for direct remaining useful life prediction. *Journal of Intelligent Manufacturing.* 27. 1-12. 10.1007/s10845-014-0933-4.

[24] **Bevilacqua, M., Braglia, M., Frosolini, M., Montanari, R.** (2005): Failure rate prediction with artificial neural networks. *Journal of Quality in Maintenance Engineering,* 11(3), 279–294. https://doi.org/10.1108/13552510510616487.

[25] **Bevilacqua, M., Braglia, M., Montanari, R.** (2003): The classification and regression tree approach to pump failure rate analysis. *Reliability Engineering and System Safety, 79*(1),59–67. https://doi.org/10.1016/S0951-8320(02)00180-1.

[26] **Braglia, M., Castellano, D., Frosolini, M., Gabbrielli, R., Marrazzini, L., Padellini, L.** (2020): An ensemble-learning model for failure rate prediction. *Procedia Manufacturing*, 42, 41–48. https://doi.org/10.1016/j.promfg.2020.02.022.

[27] **Forrester, T., Harris, M., Senecal, J., Sheppard, J.** (2019): Continuous Time Bayesian Networks in Prognosis and Health Management of Centrifugal Pumps. *Annual Conference of the PHM Society*. 11. 10.36001/phmconf.2019.v11i1.778.

[28] **Orrù, P. F., Zoccheddu, A., Sassu, L., Mattia, C., Cozza, R., Arena, S.** (2020): Machine learning approach using MLP and SVM algorithms for the fault prediction of a centrifugal pump in the oil and gas industry. *Sustainability (Switzerland)*, 12(11). https://doi.org/10.3390/su12114776.

[29] **Xiao-Sheng, S., Wenbin, W., Chang-Hua, H., Dong-Hua, Z.** (2011): Remaining useful life estimation–A review on the statistical data driven approaches, *European Journal of Operational Research,Volume 213, Issue 1*,2011, Pages 1-14, https://doi.org/10.1016/j.ejor.2010.11.018.

[30] https://www.oreda.com/handbook.

[31] **Bloch, H.P., Budris, A.R.** (2014): Pump User's Handbook, Life Extension, Fourth Edition, The Fairmont Press Inc., 2014.

[32] **Kleinbaum, D.G., Klein, M.** (2012): Survival Analysis: A Self-Learning Text. 3rd Edition, Springer, New York. https://doi.org/10.1007/978-1-4419-6646-9.

[33] **Bendell, A., Wightman, D. W., Walker, E. V.** (1991): Applying proportional hazards modelling in reliability. *Reliability Engineering & System Safety*, 34(1), 35-53.

[34] **Chen, C., Liu, Y., Wang, S., Sun, X., Di Cairano-Gilfedder, C., Titmus, S., Syntetos, A. A.** (2020): Predictive maintenance using cox proportional hazard deep learning. *Advanced Engineering Informatics,* 44, 101054.

[35] **Papathanasiou, D., Demertzis, K., Tziritas, N.** (2023): Machine Failure Prediction Using Survival Analysis. *Future Internet,* 15(5). https://doi.org/10.3390/fi15050153.

[36] **Chaoqun D., Song, L.** (2016): A Study of Proportional Hazards Models: Its Applications in Prognostics. *In Maintenance Management-Current Challenges, New Developments, and Future Directions*. IntechOpen.

[37] **Gorjian, N., Sun, Y., Ma, L., Yarlagadda, P., Mittinty, M.** (2017): Remaining useful life prediction of rotating equipment using covariate-based hazard models–Industry applications. *Australian Journal of Mechanical Engineering*, 15(1), 36-45.

[38] **Verma, A. K., Sreejith, B., Srividya, A.** (2010): Roller Bearing Defect Prognosis using Likelihood Parameters and Proportional Hazards Model. *International Journal of Performability Engineering,* 6(5), 425.

[39] **Kumar, D., Klefsjö, B.** (1994): Proportional hazards model: a review. *Reliability Engineering & System Safety,* 44(2), 177-1