Influence of Maintenance Practice on MTBF of Industrial and Mobile Hydraulic Failures: A West Balkan Study

Orošnjak, Marko[1[0000-0003-0929-1425]], Delić, Milan[1[0000-0002-3307-8942]], Ramos, Sandra[2[0000-0001-5788-1679]]

[1] University of Novi Sad, Faculty of Technical Sciences, Trg Dositeja Obradovića 6, 21000 Novi Sad, Serbia
[2]Instituto Politécnico do Porto, Instituto Superior de Engenharia, R. Dr. António Bernardino de Almeida, 431, Porto, Portugal
orosnjak@uns.ac.rs

Abstract: The article investigates the influence of maintenance practice on the MTBF (Mean-Time-Between-Failures) of hydraulic systems. Firstly, the paper starts by challenging the argument that contamination is at least 70% responsible for hydraulic system failures. Secondly, independent maintenance variables that potentially influence MTBF are synthesised and investigated via Person's correlation factor. Although some predictors (variables) show good prediction properties, however, show discrepancy while being subjected to different maintenance policies. Eight selected predictors were subjected to Stepwise Multiple Regression (SMR) for selecting the most appropriate solution. Finally, four main predictors ($p < .05$) are selected: Machine Age (MA), Filter Replacement Time (FRT), Failure Analysis Personnel (FAP) and Maintenance Policy (practice) (MP) applied. The results show that the suggested model shows good prediction properties ($R^2=83.51$) in estimating the MTBF of hydraulic systems.

Keywords: contamination control, filter management, mean-time-between-failures, hydraulic failures, stepwise multiple regression, maintenance policy

1 Introduction

It has been an ever-present notion that the most common cause of failures in hydraulic systems is contamination [1]. Divided opinions of engineers and scientists stating that between 70-90% [2–4] of failures attributes to contamination (solid particles [5], air and water contamination [6], temperatures [7]) resonate with the need for more up-to-date evidence on the matter. Such statements suggest that hydraulic system reliability [8] is strongly associated with the fluid condition [9]. Consequently, this causes the actuator's response rate and precision, thus the product quality [10]. Therefore, one would expect that MTBF (Mean-Time-Between-Failures) depends on Maintenance Decision-Making (MDM) at the operational and tactical levels, thus encompassing the importance of the Maintenance Analysis Program (MAP), for instance, oil condition monitoring (OCM) [11] or Prognostics and Health Management (PHM) [12] in reducing MTBF. At the strategic level, there is a lack of evidence that compares the value of

MTBF subjected to different MP (Maintenance Policy). However, assuming that innovative policies improve MTBF, studies highlight the cases where the most advance MP does not always show the best performance. For instance, Sellitto [13] investigated the influence of opportunistic, corrective and preventive maintenance policy performance. The study shows that corrective maintenance outperforms opportunistic and partial corrective. Vineyard et al. [14] study the influence of five MPs on flexible manufacturing system (FMS), showing that the opportunistic maintenance policy outperforms preventive and corrective policies. In a recent study, Paprocka et al. [15] pointed out that frequent maintenance actions reduce overall maintenance performance, questioning companies' ability to adapt CBM considering the trade-off between reducing stoppages and increasing profit.

To follow up on the maintenance practice perturbations and the influence on MTBF, specifically in an oil hydraulics sphere, we first challenge the argument that contamination is at least 70% ($P \geq .70$) responsible for the hydraulic system' failures (***hypothesis – H_1***). From our practical experience, pipes and hoses' bursting is the most common component failure. However, if the contamination is still a relatively high cause of failure, we can presume that filter replacement time (FRT) must have a strong correlation ($r > .5$, $p < .01$) with MTBF (***H_2***) given the sample size. Since our focus group comprises the companies utilising hydraulic systems, the study eligibility criteria consider filter replacement practice regardless of the policy. Therefore, we set the final hypothesis as (***H_3***): "Maintenance policy does not play a significant role as a predictor in regression modelling" (with $p > .05$).

This study aims to provide a clear understanding of the maintenance practice effect on MTBF's with a specific regression model considering predictors of interest. Three additional research objectives are defined for accomplishing the study aim: (1) develop a questionnaire-based instrument for collection of empirical evidence for a defined time-span; (2) determine critical predictors using stepwise multiple regression (SMR); (3) validate the model through hypothesis testing. The rest of the study is as follows. Section 2 explains the general research model and methodology used for setting the research context. Section 3 depicts the questionnaire meta-data, failure-related and maintenance-related empirical evidence on the West Balkan territory, and the research findings. The final section encapsulates the research findings and proposes future research agenda.

2 Methodology

The questionnaire-based survey is set for the region of West Balkan territory. The survey is disseminated to the companies explicitly utilising hydraulic mobile and industrial systems for servicing and manufacturing purposes. The questionnaire instrument validation is developed through three stages (**Fig. 1**): (1) survey design – literature review, determining variables, and expert judgment (panel 1); (2) survey simulation – setting region, period, and focus group to determine if the survey is understandable and if variables can be measured (panel 2); (3) survey analysis – meta-data, data sorting and filtering in respect to eligibility criteria, and evaluation of empirical evidence collected.

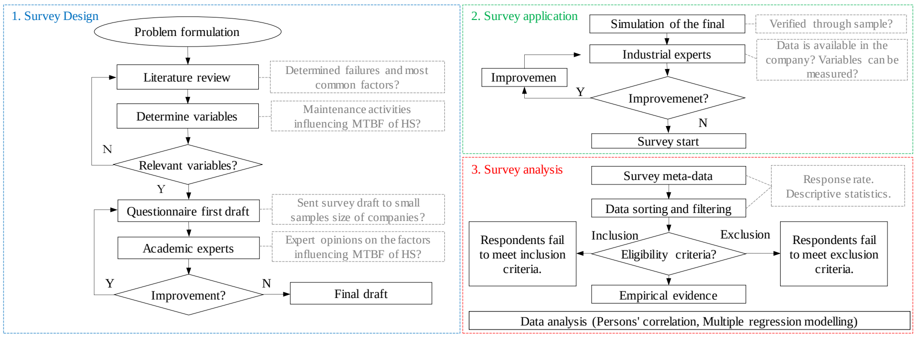

Fig. 1. Survey design and general research model

Additionally, companies willing to share the data could bypass the survey if all the data available is appropriate. As stated, MTBF served as a function for investigating latent maintenance variables affecting the result. Aside from machine age (MA), the maintenance variables collected for estimating the influence on MTBF include maintenance personnel per machine (MPPM), Maintenance Department Team (MDT), Failure Analysis Personnel (FAP), Filter Replacement Time (FRT), Condition Monitoring Sensors (CMS), Oil Replacement Time (ORT), MP and MAP.

Based on the data, we presume that the systems are in a somewhat mean exploitation stage of the bath-tub curve and not in the early (infant) nor wear-out stage since models show good prediction properties as a linear function. Therefore, with statistically significant confidence, we can confirm that the MTBF can follow the proposed model's linearity if, and only if, the fundamental assumptions are confirmed – linearity, multivariate normality, absence of multicollinearity and homoscedasticity. The multivariate normality of regression analysis assumes that the residuals are normally distributed. Multicollinearity assumes that independent variables are not highly correlated, which can be confirmed using Pearson's correlation (< *.80*). Homoscedasticity assumes that the error variance is similar across independent variables. The plot shows if the points are equally distributed around the dependent variable. Finally, to determine the maximum number of predictors used for the regression model, we used a rule of thumb that a sample should be between 5-15 per variable (predictor).

3 Results and discussion

The survey results show a 37% response rate from 220 companies in the evaluation realised between May 2018 to September 2019 on West Balkan's territory. However, after analysing the data and concerning eligibility criteria, 18 respondent applications were flagged as ineligible. In the final 63 survey applications (1153 hydraulic machines) were eligible for the analysis of which 31 companies were from the manufacturing sector, while 32 companies were from construction, open- and closed-mining sectors.

Given the results, the evidence suggests that the most common failures are hoses and pipes (**Fig. 2**). Thus, to test the claim that the most common cause of failure is contamination (H_1, $P \geq .70$), we used a z-test statistic for one sample proportion. The data shows that contamination is responsible for 37,98% of failures as a sum of contamination due to air, water, temperature, and solid particles (**Fig. 2**). Thus, the test statistic shows the following results:

$$z = \frac{\hat{P}-P}{\sqrt{\frac{P \cdot q}{n}}} = \frac{0.3798-0.7}{\sqrt{\frac{0.7 \cdot 0.3}{1153}}} = -23.73. \quad (1)$$

The *z* score shows the *p-value* < *.01*; therefore, we can reject the H_1 at a significance level of at least 1%.

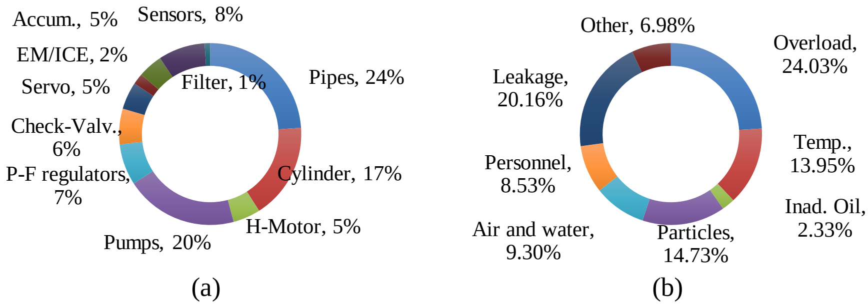

Fig. 2. Most common component failures (a) and the most common causes of failures (b)

To test the relationship between FRT and MTBF, we used Pearson's test statistic (**Table 1**) to determine the correlation between the variables. The results show that variables MA, FRT, FAP and MP show a strong correlation (*p* < *.01*) with resulting MTBF function, while MAP and MDT show lower tendency with *p* < *.5* and < *.1*, respectively. Thus, the value of *–.65* (p < .01) shows a high negative correlation of FRT and MTBF, by which case H_2 is proven and accepted as valid.

Table 1. Pearson's correlation matrix of potential factors influencing MTBF

	MTBF	MP	MAP	MPPM	MDT	FAP	MA	FRT
MTBF								
MP	.40***							
MAP	.26**	.41***						
MPPM	-.06	-.05	.18					
MDT	.18*	.18*	.11	-.01				
FAP	.48***	.37***	.13	-.06	.36***			
MA	-.83***	-.21*	-.14	.18	-.02	-.36***		
FRT	-.65***	-.20	-.16	-.03	-.24*	-.45***	.58***	
CMS	.13	.04	.21*	.11	-.10	.13	-.25**	-.21*

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; CMS = Condition Monitoring Sensor. *p*-value < .01***, *p*-value < .05**; *p*-value < .1*

Displayed results show a low *p*-value of MDT, MPPM and MAP, and after running an SMR in MINITAB and using ANOVA, the coefficients show the *p-value* > *.05* and are excluded from the modelling. Besides, we ran a Grubbs test for outliers and used a scatter plot to check for linearity. The scatter plot shows good linearity, and the outlier test (G = 1.91) shows the absence of outliers. The second assumption is to check multivariate normality, i.e. errors of observed and predicted values are normally distributed (**Fig. 3** – Normal Probability Plot). The third assumption is to check the absence of multicollinearity, which is proven with no coefficients between independent variables $r > .80$ (**Table 1**). The final assumption is to check for heteroscedasticity in the data. The expansion in the model's linearity suggests heteroscedasticity, and data, in this case, is homoscedastic (**Fig. 3** – Versus Fits; Versus Order).

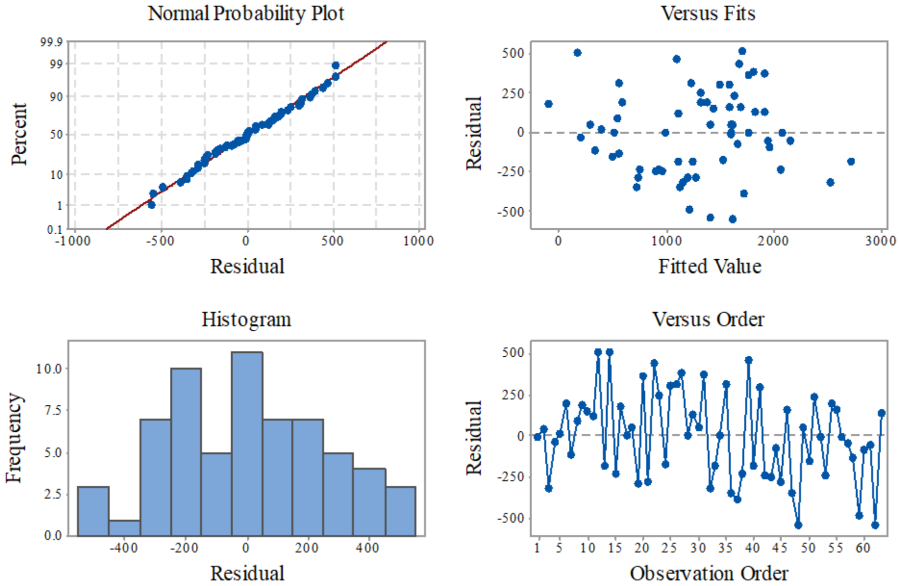

Fig. 3. MTBF residuals testing the predicted and observed value

After elaborating and confirming linearity assumptions, a general MLR analysis model is formulated as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon \,. \quad (2)$$

Additionally, for multiple non-linear regression, we used exponential regression as:

$$y = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon) \quad (3)$$

The y is the dependent variable, x_i are independent variables, β_i are maintenance parameters/coefficients, and ε is the error ~ $N(\mu, \sigma^2)$. $MTBF_{NLR}$ model is an exponential function model, and $MTBF_{LR}$ is a multi-linear model with the function of MTBF modelled from coefficients in **Table 1**. Since FAP and MP variables are qualitative expressions, the predictors are categorical (dummy) variables (0, 1). The resulting models are represented in the following equations.

$$MTBF_{NLR} = e^{8.641 - 0.1119 \cdot \mathrm{MA} - 0.000132 \cdot \mathrm{FRT} + \mathrm{MP} + \mathrm{FAP}} \quad (4)$$

$$MTBF_{LR} = 3112 - 0.1052 \cdot FRT - 100.2 \cdot MA + MP + FAP \tag{5}$$

Table 2. Resulting R^2 values for MLR and MNLR optimised models

Model	*S*	R^2	R^2_{adj}	R^2_{pred}
$MTBF_{NLR}$	0.329	81.45%	77.88%	69.73%
$MTBF_{LR}$	287.294	83.51%	80.34%	75.17%

Both models show good R^2 and R^2_{adj} values; however, prediction properties of R^2 show a relatively high deviation with the exponential case (**Table 2**). Finally, we used ANOVA analysis (**Table 3**), showing that MP ($p < .05$) rejects the hypothesis (**H_3**) and shows that the influence of MP as a predictor is significant in the case of $MTBF_{LR}$. In exponential case, SMR excludes candidate predictor MP because the *p-value* > .05. The results show that the MP' coefficients of individual policies significantly affect ($p < .05$) in improving the R^2 of the $MTBF_{LR}$ model (**Table 4**).

Table 3. ANOVA results of coefficients in optimised MLR and MNLR model

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Multiple non-linear regression model ($MTBF_{NLR}$)					
Regression	10	24.7028	2.4703	22.83	.000
FRT	1	.5450	.5450	5.04	.029
MA	1	7.9028	7.9028	73.05	.000
MP	4	.8808	.2202	2.04	.103
FAP	4	1.2177	.3044	2.81	.034
Error	52	5.6258	.1082		
Total	62	30.3285			
Multiple linear regression model ($MTBF_{LR}$)					
Regression	10	21733903	2173390	26.33	.000
FRT	1	348134	348134	4.22	.045
MA	1	6338796	6338796	76.80	.000
MP	4	1648447	412112	4.99	.002
FAP	4	1191207	297802	3.61	.011
Error	52	4291981	82538		
Total	62	26025884			

For more in-depth analysis and discussion of MP and FAP coefficients, the data is given in **Table 4**. There are individually five categorical variables of both MPs and FAP. The linear model's function shows that the best policy is CBM, while other policies show degradation in MTBF given in coefficients. The worst policy for maintaining hydraulic systems is DM. We suspect that engineers in redesigning or modifying the equipment did not consider the MDT and expertise of FAP in later removal or reducing the equipment failures. The FBM also shows a result of a 574h reduction in the MTBF indicator. The PM shows a slight reduction of 467h in the MTBF indicator, whereas OM shows the lowest 400h reduction. Indeed, CBM shows the best performance compared to other policies, suggesting that condition monitoring in predictive analytics and reducing stoppages plays an important role in increasing the availability of hydraulic systems.

Table 4. $MTBF_{LR}$ model-independent continuous and categorical coefficients

Term	Coefficient	SE Coeff.	T-value	P-value	VIF
Constant	3112	176	17.66	.000	
MA	-100.2	11.4	-8.76	.000	1.66
FRT	-.1052	.0512	-2.05	.045	1.84
MP					
CBM	0	0	*	*	*
DM	-800	209	-3.83	.000	1.51
FBM	-574	156	-3.68	.001	2.68
PM	-467	131	-3.57	.001	3.07
OM	-400	194	-2.06	.045	1.71
FAP					
Engineer	0	0	*	*	*
None	-156	134	-1.16	.251	2.12
Outsource	-46	114	-.41	.686	2.19
Specialist	145	157	.92	.361	1.62
Technician	-368	128	-2.88	.006	2.15

Note: Maintenance Policies – CBM = Condition-Based Maintenance; DM = Design-Out Maintenance; FBM = Failure Based Maintenance; OM = Opportunity Maintenance; PM = Preventive Maintenance. VIF – Variance Inflation Factor. SE Coeff. – Standard Error Coefficient.

Considering the FAP, the failure analysis is divided into five categories. The best performance on the MTBF indicator is if a specialist performs failure analysis. Engineer show no effect on MTBF improvement nor reduction. Outsourcing failure analysis shows a reduction of 46h in MTBF, while if there is no failure analysis personnel, i.e. if parts are replaced in the "as-good-as-new" approach, the 156h reduction MTBF is observed. Finally, if failure analysis performs a technician on the "as-bad-as-old" basis, the evidence suggests the highest MTBF reduction by 368h. Overall, it can be said that accurate analytics plays one of the most crucial roles in reducing the MTBF of a hydraulic system. Inappropriate failure analysis by unspecialised personnel leads to the escalation of MTBF, or in the cases of a replacement of the parts on "an as-good-as-new" basis leads to more financial investments.

4 Conclusion

The lack of recent studies on the causes of hydraulic failures provoked the authors to conduct the study. Current findings suggest that contamination is still the primary cause of failures at a much lower proportion. However, although system overload and personnel mistakes are considered the causes of failure, an intrinsic relationship with contamination is present. This is because it is impossible to isolate and provide an exact reproduction of particular conditions of failure; even though the study included 63 companies utilising 1153 hydraulic machines, the research may be impeded by the lack of complete details surrounding failure causes in practice. The fact that FRT plays a significant role in MTBF reduction stress this implicit causality. Finally, the model highlights that coefficients (MP and FAP) are statistically significant predictors in improving the R^2_{adj} value. Further research includes an in-depth exploration of the causality between MTBF and maintenance practice on all MDM levels.

References

1. Espinosa-Garza, G., De Jesus Loera-Hernandez, I.: Improvement of productivity in hydraulic systems with servomechanisms. Procedia Manuf. 41, 779–786 (2019). https://doi.org/10.1016/j.promfg.2019.09.070
2. Ng, F., Harding, J.A., Glass, J.: Improving hydraulic excavator performance through in line hydraulic oil contamination monitoring. Mech. Syst. Signal Process. 83, 176–193 (2017). https://doi.org/10.1016/j.ymssp.2016.06.006
3. Tič, V., Edler, J., Lovrec, D.: Operation and accuracy of particle counters for on-line condition monitoring of hydraulic oils. Ann. Fac. Eng. Hunedoara. 425–428 (2012)
4. Mariusz, D., Hassan, M., Joanna, D.: Simulation of Particle Erosion in a Hydraulic Valve. Terotechnology. 5, 17–24 (2018). https://doi.org/10.21741/9781945291814-4
5. Karanović, V., Jocanović, M., Baloš, S., Knežević, D., Mačužić, I.: Impact of contaminated fluid on the working performances of hydraulic directional control valves. Stroj. Vestnik/Journal Mech. Eng. 65, 139–147 (2019). https://doi.org/10.5545/sv-jme.2018.5856
6. Baker, M.: Most Common Causes of Hydraulic Systems Failure, https://yorkpmh.com/resources/common-hydraulic-system-problems/
7. MACHydraulics: Effects of Temperature on Hydraulic Systems, https://mac-hyd.com/blog/hydraulic-system-temperatures/
8. Orošnjak, M., Jocanović, M., Karanović, V.: Quality analysis of hydraulic systems in function of reliability theory. In: Annals of DAAAM and Proceedings of the International DAAAM Symposium (2016)
9. Jocanovic, M., Agarski, B., Karanovic, V., Orosnjak, M., Ilic Micunovic, M., Ostojic, G., Stankovski, S.: LCA/LCC Model for Evaluation of Pump Units in Water Distribution Systems. Symmetry (Basel). 11, 1181 (2019). https://doi.org/10.3390/sym11091181
10. Runje, B., Horvatic Novak, A., Keran, Z.: Impact of the Quality of Measurement Results on Conformity Assessment. In: 29th DAAAM International Symposium on Intelligent Manufacturing and Automation. pp. 0051–0055. DAAAM International Vienna (2018)
11. Karanović, V. V, Jocanović, M.T., Wakiru, J.M., Orošnjak, M.D.: Benefits of lubricant oil analysis for maintenance decision support: a case study. In: IOP Conference Series: Materials Science and Engineering. pp. 1–8. IOP Publishing (2018)
12. Orošnjak, M., Jocanović, M., Karanović, V.: Applying Contamination Control for Improved Prognostics and Health Management of Hydraulic Systems. In: Smart Innovation, Systems and Technologies. pp. 583–596 (2020)
13. Sellitto, M.A.: Analysis of maintenance policies supported by simulation in a flexible manufacturing cell. Ingeniare. 28, 293–303 (2020). https://doi.org/10.4067/S0718-33052020000200293
14. Vineyard, M., Amoako-Gyampah, K., Meredith, J.R.: An evaluation of maintenance policies for flexible manufacturing systems. Int. J. Oper. Prod. Manag. 20, 409–426 (2000). https://doi.org/10.1108/01443570010319156
15. Paprocka, I., Kempa, W.M., Skołud, B.: Predictive maintenance scheduling with reliability characteristics depending on the phase of the machine life cycle. Eng. Optim. 53, 165–183 (2021). https://doi.org/10.1080/0305215X.2020.1714041