Decision making process to evaluate the optimum power unit maintenance in hydraulic excavators

SAKI GERASSIS[1], JULIO F. GARCÍA[1], ÁNGELES SAAVEDRA[2], JOSÉ E. MARTÍN[1] and JAVIER TABOADA[1]
[1]Department of Natural Resources and Environmental Engineering
[2]Department of Statistics and Operational Research
University of Vigo
Lagoas Marcosende, 36310 Vigo, Galicia
SPAIN
sakis@uvigo.es, juliogarcia@uvigo.es, saavedra@uvigo.es, jmartinsuarez@uvigo.es, jtaboada@uvigo.es

Abstract: - The power unit is the fundamental element of hydraulic excavators. Its actual technological evolution derives in a design complexity that makes it difficult either for mining constructors or engineers to predict accurately its failure. For this reason, the main objective of this work is to provide a suitable decision model to obtain the probability distribution that better reflects the fault occurrence on the power unit for mining excavators from a work management perspective. The proposed method relies on the probabilities for each fault typology in the power unit estimated from data of faults collected in different mining excavators throughout its operation life. An optimum maintenance strategy is modelled through an influence diagram in terms of repair costs and production losses, representing the direct and indirect costs engineers have to face when a machine breaks down. An interesting result is the identification of the probabilistic model that best reflects the estimation of prior fault probabilities of the power unit elements. Surprisingly, indirect costs due to lack of production are found to be about 4.5 times bigger than direct costs, reflecting the necessity for a maintenance strategy capable to reduce faults in the early stages avoiding costs to become expansive over time. The application of this decision model helps to minimize production losses at the same time engineers gain knowledge about the risk attitudes that boost an efficient management of uncertainties involved with the severity and time of appearance of certain types of faults.

Key-Words: - Decision making, hydraulic excavator, maintenance, systems reliability, mining engineering, risk tolerance, power unit.

1 Introduction

Excavators (Hydraulic Excavators) are heavy construction equipment decisive for earthmoving operations both in mining and civil works. They are most commonly used for digging rocks and soil, but with its many recent attachments can also be used for cutting steel, breaking concrete, drilling holes in the earth or laying gravel onto the road prior to paving [1].

Power in an automobile is normally received straight from the engine but in a hydraulic excavators this is different. Because the machine uses a lot of force, the power unit is able to move by changing the energy it receives from the engine into hydraulic power [2]. The engine consists of three parts. The engine block, the engine head and the lower engine. Each part is constituted respectively for a large number of components which are assembled in order to obtain the intended part. When talking about failures, from the set of faults that can be recorded during the machine´s service life, according to their prevalence, those that can be associated with the power unit can be classified as: direct engine faults, injection system faults and starter engine faults.

During the past 20 years there has been a heightened improvement in the manufacture of heavy machinery engines [3]. They are more powerful and fuel efficient with a minimized impact of emissions. The reliability has also been significantly enhanced with the inclusion of sophisticated electronic settings able to detect and predict nearby faults, but with a high price. Commonality and simplicity of design has turned now into complex structures with multiple sensors and an increased number of components. On many occasions, when faults occur time to repair takes a considerable time due to disassembly process which has to be carried out by qualified technical staff.

However, from a management perspective when a fault occurs the problem for engineers is not so much which component has failed, rather than how long is going to be the machine stopped or how much is the reparation cost. This situation, creates the necessity to define maintenance strategies oriented toward a wider scale represented by the set of power unit elements failure instead of power unit components failure. This new approach provides a great simplification of the domain problem, although a commonly held view is that the decision-model results and conclusions are only as good as the distributions that go into it.

To summarize the foregoing discussion, inaccurate questions always tend to ask which is the correct distribution to use for a specific topic. The motivation behind this work comes from trying to figure out whether different distributions change in a considerably way our maintenance decisions. Moreover, a range of possible attitudes can be adopted towards the same risk situation, resulting in different maintenance behaviours, which lead to production consequences. In this context, this paper evaluates exponential and Weibull distributions due to its extensive use in data analysis and reliability engineering [4]. The exponential distribution excels by its simplicity in calculation, but might not be appropriate to model the overall lifetime power unit elements, because the failure rates are not constant, and a constant failure rate approximation could not be representative enough. Alternatively, an important aspect of the Weibull distribution is how the values of the shape parameter k and the scale parameter λ affect the probability density function (PDF) and how they properly represent the power unit reliability [5]. For this latter issue, an accurate estimation of Weibull parameters is needed in order to obtain a reliable analysis of the occurrence of faults in the power unit.

The rest of the paper is structured in the following way. Section 2 presents the mathematical methods used to determine Weibull parameters and obtain the cumulative distribution function (CDF), both for Weibull and exponential distribution. Section 3 explains the influence diagram design for maintenance assessment in hydraulic excavators. Section 4 shows the decision model results and discusses the findings obtained about how these distributions may influence maintenance decisions and attitude towards risk. Section 5 concludes the paper and provides future work addressing the urgency of developing new models and systems that improve heavy machinery performance.

2 Problem formulation

The Weibull distribution is an appropriate probability distribution for modelling survival analysis and has been widely used in reliability engineering and failure analysis due to its versatility. The density function of a Weibull distribution is given by the following expression:

$$f(x_i|\theta) = \frac{k}{\lambda}\left(\frac{x}{k}\right)^{k-1} e^{-(x/\lambda)^k}, x \geq 0, \qquad (1)$$

where $\theta = (k, \lambda)^t$, $k > 0$ is the shape parameter, $\lambda > 0$ the scale parameter and t denotes transposed. On the other hand, the exponential distribution is a particular case with $k = 1$ indicating a constant failure rate $\eta > 0$ over time and, therefore, that random external events are causing the components failure.

2.1 Estimation methods

In order to select the probabilistic model that best reflects this new approach to determine the fault of the power unit in mining excavators, several methods have been implemented for the estimation of the parameter θ. Given a sample $\{x_1, x_2, \dots, x_n\}$ of size n drawn from a random variable X, the following estimation methods can be defined:

Method 1. Maximum likelihood estimation. Under i.i.d. assumption, θ is estimated by maximizing the likelihood function defined as:

$$L(\theta) = \prod_{i=1}^{n} f(x_i|\theta). \qquad (2)$$

Method 2. Moment matching estimation. This technique is based on matching the sample moments with the corresponding distribution moments:

$$E(X^r) = \frac{1}{n}\sum_{i=1}^{n} x_i^r, \qquad r = 1,2. \qquad (3)$$

Method 3. Quantile matching estimation. Based on matching the sample moments with the corresponding distribution moments:

$$F^{-1}(p_r|\theta) = Q_{n,p_r}, \qquad 0 < p_r < 1. \qquad (4)$$

Method 4. Maximum goodness-of-fit estimation with the Cramer-von Mises goodness-of-fit distance. Assuming that an ordered sample, $x_1 \leq x_2 \leq \cdots \leq x_n$, θ is estimated by minimizing:

$$\frac{1}{12n} + \sum_{i=1}^{n} \left(F(x_i|\theta) - \frac{2i-1}{2n} \right)^2 \qquad (5)$$

Method 5. Maximum goodness-of-fit estimation with the Kolmogorov-Smirnov goodness-of-fit distance. Assuming that an ordered sample, $x_1 \leq x_2 \leq \cdots \leq x_n$, θ is estimated by minimizing:

$$max\left\{ \max_{i=1,\dots,n} \left(\frac{1}{n} - F(x_i|\theta) \right), \max_{i=1,\dots,n} \left(F(x_i|\theta) - \frac{i-1}{n} \right) \right\} \qquad (6)$$

2.2 Goodness of fit statistics

The goodness of fit of a statistical model describes how well it fits a set of observations. Different goodness of fit statistics were calculated to measure the distance between the adjusted parametric distribution and the empirical distribution. Firstly, three goodness of fit statistics which are classically considered when fitting continuous distributions: Cramer-von Mises, based on (5), Kolmogorov-Smirnov, whose distance was given in (6), and Anderson-Darling with the following goodness of fit distance, assuming an ordered sample:

$$n - \frac{1}{n}\sum_{i=1}^{n} (2i-1)\, log\left[F(x_i|\theta)\left(1 - F(x_{n+1-i}|\theta)\right)\right] \qquad (7)$$

Secondly, the loglikehood criteria such as the Akaike information criterion or the Bayesian information criterion are often appropriate to avoid overfitting when small samples are available:

$$AIC = 2r - 2ln\left[L(\hat{\theta})\right], \qquad (8)$$

$$BIC = ln(n)r - 2ln\left[L(\hat{\theta})\right], \qquad (9)$$

with *r=2*, number of estimated parameters.

Finally, root mean square error:

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^{n} \left(f(x_i|\hat{\theta}) - \frac{1}{n} \right)^2 \right]^{1/2} \qquad (10)$$

and Chi-squared distance:

$$\chi^2 = \frac{\sum_{i=1}^{n} \left(f(x_i|\hat{\theta}) - \frac{1}{n} \right)^2}{n-r} \qquad (11)$$

were also calculated.

2.3 Estimated parameters and selected probability distributions

All calculations were obtained using the open source programming language R [6]. The results obtained with the different goodness of fit statistics allowed to identify Method 5 for the engine, Method 1 for the starter engine and Method 3 for the injection system as the best estimation methods for the obtainment of Weibull parameters. The values of the parameters required for the representation of the cumulative distribution function for each power unit element with the winning methods are shown in Table 1.

Note that the cumulative distribution function for the Weibull distribution is:

$$F(x) = 1 - e^{-\left(\frac{x}{\lambda}\right)^k}, x \geq 0, \qquad (12)$$

whose representation requires the estimation of the scale λ and shape κ parameters. Whereas, the exponential distribution only needs the failure rate η, being its cumulative distribution function:

$$F(x) = 1 - e^{-\eta x}, x \geq 0. \qquad (13)$$

In Table 1 is shown the constant failure rate for each power unit element made as an approximation of the average of faults in the machine's operating life. It is interesting to analyse the payoff between its simplicity of calculation and the magnitude of the difference in the results, Figure 1, especially when they are transferred to an influence diagram affecting strategic decisions.

Table 1: Parameters values for Weibull and exponential distributions representation

Weibull Distribution		
	Shape (κ)	Scale (λ)
Engine	0.91290	1222.22
Starter Engine	1.44447	3244.58
Injection System	1.94212	3658.132
Exponential Distribution		
	Failure Rate (η)	
Engine	0.00027586	
Starter Engine	0.00015517	
Injection System	0.00012069	

In view of Figure 1, it can be seen how the Weibull distribution gives higher probabilities to the failure of the units during the first years of tis operating time. From the middle operating time of the machine the probabilities show more similar results being the difference less noticeable.

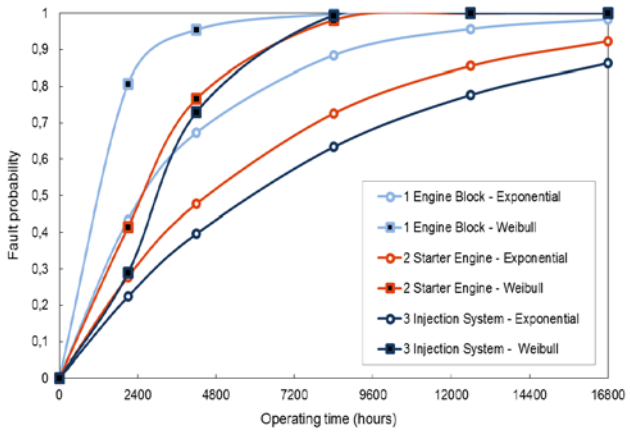

Fig.1: Cumulative distributions functions comparison for the power unit elements.

3 Influence diagram for maintenance strategy evaluation

The maintenance strategy is modelled through an influence diagram (ID). An ID is a directed acyclic graph representing a generalization of a Bayesian network, in which probabilistic inference can be applied to solve decision making problems [7]. IDs are directly applicable in team decision analysis since it allows sharing of information among team members to be modelled and solved explicitly. Several extensions of IDs find their use in game theory as an alternative representation of decision trees.

3.1 Semantics and design

In this case, the ID was created using the decision modelling software BayesFusion, LLC [8]. The problem design depicted in Figure 2 involves 4 variable types for notation:

- 2 decision nodes (green rectangles). The *excavator operating time* is evaluated in hours. Every operation year the excavator works 4,800 hours, considering a service life at full performance up to 16,800 hours. The *maintenance strategy* node offers the possibility to assess the maintenance strategy according to the fault probabilities for each element of the power unit obtained with exponential and Weibull distributions (Figure 2).

- 3 chance nodes (yellow circles). The *engine* itself, the *starter engine* and the *injection system*. They are quantified by the probabilities (Figure 1) which integrate the uncertainty associated to the failure of the power unit.

- 1 deterministic node (red double circle). It represents the *fault severity* of the power unit. Once all their parents are known, there is no uncertainty about the outcome. The quantification is similar to chance nodes [9]. The only difference now is that when a fault event takes place, the outcome is known with certainty. The definition is done with a probability table (Table 2) that contains the fault severity depending on the combination of fault elements in the power unit, according to the criteria of mining engineers consulted.

Table 2: Deterministic node definition. Fault occurrences (✓) determining power unit fault severity (very high, high, medium or low).

	Engine	Starter Engine	Injection System
Very High	✓	✓	✓
	✓		✓
High	✓	✓	
	✓		
		✓	✓
Moderate			✓
Low		✓	

- 8 value nodes (blue and red hexagons). Blue hexagons represent the direct cost (DC) and red hexagons the indirect cost (IC) for each power unit element fault. DCs refer to the economic cost of fault repair. On the other hand, ICs imply a broader concept. They compute the economic cost associated with the loss of production due to the failure of the machine. The loss of production depends on the repair time, which is in turn dependent on the severity of the fault. For this reason, the utility costs for every element fault are computed independently. This approach allows to figure out which element is causing the highest lost. However, for a generalized analysis it is usually easier for the decision maker to combine them in a single multi-attribute utility function (MAU) [10]. Thus, the influence diagram has two final MAUs, the Power Unit DC and the Power Unit IC, summarizing the direct and indirect costs expected for the power unit elements failure over time. In this way, any strategy change on the decision nodes will be directly computed giving rise to a final result represented by the MAUs.

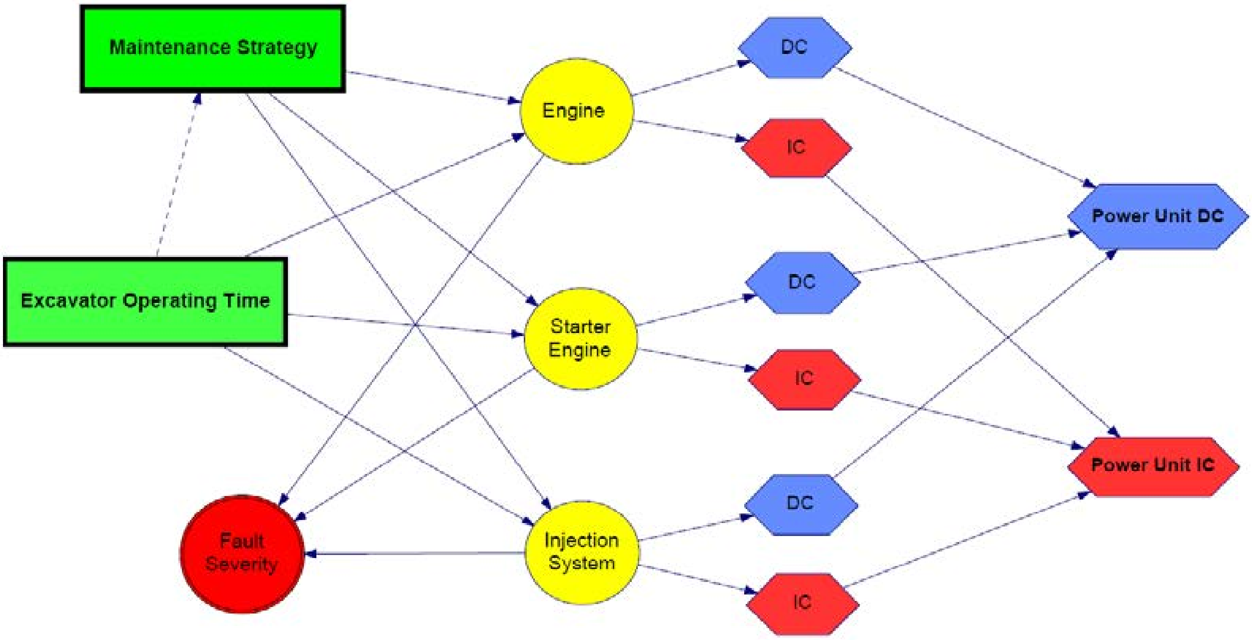

Fig.2: Influence diagram (ID) for power unit maintenance evaluation of hydraulic excavators

3.2 Relation with the expected utility theory

In accordance with the expected value criterion, which takes into account only the sizes of the payouts and the probabilities of occurrence, the goal of an influence diagram is to highlight a decision alternative that has the highest expected gain or utility [5]. Utility is, however, by assumption subjective. In this particular case, the influence diagram enables engineers and decision makers assess the expected costs of suffering a failure over time. This approach means that direct and indirect costs need now to be minimized knowing that the maintenance and failure duo has not a meaningful zero point because maintenance has always an associated cost and it is very rare the case, not to say impossible, that an excavator has no faults during its operating time, no matter how good the maintenance could be.

Various decision makers facing the same problem and even sharing the same set of beliefs may choose differently because of their preference structure and different utility functions, although they are under the same uncertain situation. This can be especially noticed in a field such as engineering. A human decision maker does not always choose the option with the higher expected value. According to the expected value theory engineers here should choose the strategy that minimizes the faults occurrence although the maintenance cost is higher.

However, as stressed by expected utility theory, some engineers will adopt risk-averse decisions, even though the expected value is lower. Others will make risk-seeking decisions, identifying fewer threats and looking for a bigger reward. Sometimes the best solution lies somewhere in between. A risk neutral attitude are neither risk-averse nor risk-seeking, but rather seek strategies and tactics that have the highest future pay-offs, focusing on the longer term and only taking action when it is likely to lead to significant benefit.

4 Decision model results

The results obtained offer two principal contributions. Firstly, how the estimations of prior probabilities can affect decision making for maintenance policy in this new approach based on the power unit segmentation into three main failure elements. Secondly, how the risk for fault severity changes depending on the model selected.

4.1 Distribution influence on decision making

The expected direct and indirect costs associated with the failure of the power unit modelled either with exponential or Weibull distribution show a significant growth in the first two years (see Figure 3 and 4). After the second year, when the machine has been operating more than 9600 hours, the expected costs present a certain stabilization.

Comparing the results obtained with each model, a big difference lies within the first 3 years. The influence diagram when is modelled with exponential distribution gives rise to lower direct and indirect costs for that period. These differences reduce over time, from 48% less for the first year to 20% less the second and just 10% less the third. This highlights that even if both models present a good similarity from the third year onwards, Weibull distribution, more accurate mathematically, can better respond to the expected costs during the initial stages. Therefore, even though for some real life scenarios a constant failure rate can represent a good approximation, a Weibull distribution has proven to be a worthwhile distribution for modelling power unit faults, although the estimations of its parameters may be more time-consuming in terms of calculation.

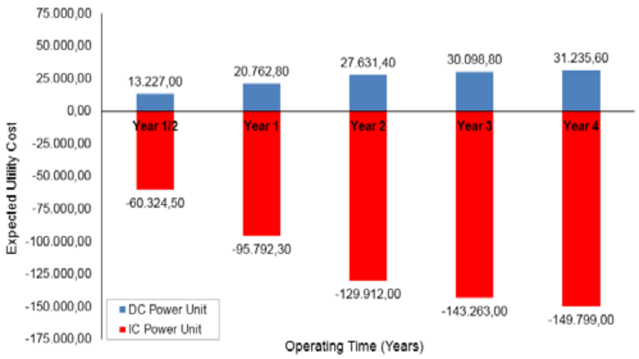

Fig.3: Direct and indirect expected fault costs for the exponential probabilistic model

This last point is also supported by the fact that Weibull distribution enables a better understading of power unit elements. The shape parameter κ represents the failure rate behaviour. A value of $\kappa < 1$ indicates that the failure rate decreases over time. This is the case of the engine $\kappa = 0.91290$ (Table 1). When $\kappa > 1$ the failure rate increases with the passing of time. The starter engine $\kappa = 1.44447$ and the injection sysmtem $\kappa = 1.94212$ (Table 1) present this condition reflecting the existence of an aging process. It is noticeable that the engine itself is the one with the most similar behaviour to an exponential distribution ($\kappa = 1$), while the injection system gets closer to a Rayleigh distribution ($\kappa = 2$) with the starter engine in the middle of these two.

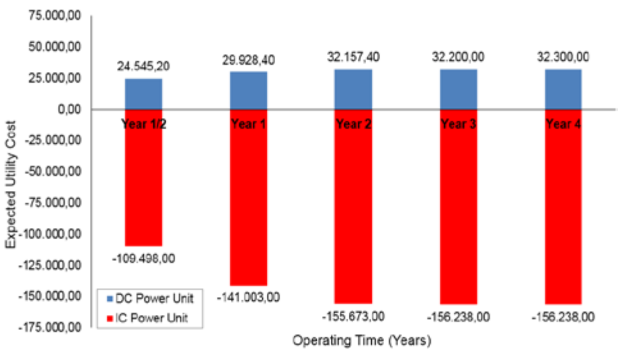

Fig.4: Direct and indirect expected fault cost for the Weibull probabilistic model

When designing an optimum maintenance policy this knowledge is crucial. The engine is known now as more sensitive to suffer initial faults, while the starter engine and the injection system present the inverse condition. A right balance could be found with an extensive maintenance that pays special attention to the machine in its initial stage moving toward a less exhaustive maintenance when the machine have reached its half-life. This could ensure a good adaptation of the engine to the work environment whilst promoting a healthy aging for the starter engine and the injection system.

From a management perspective this can be understood knowing that a fault minimization at the beginning of the excavator operating life not only involves a reduction in direct costs associated with repair, but also would contribute to quickly reach the required hours to complete the amortization of the machine without suffering faults.

Undoubtedly, a surprising result is he one related to the indirect costs. Indirect costs show up in a ratio of 4.5 to 1 compared with direct costs. They are larger from what many engineers can imagine, often hidden behind the shadow of the faults having a huge role system performance. A reasonable explanation for the big magnitude of indirect costs can be found in the fact that when an excavator breaks down the operative process has to stop. The lack of an operative excavator prevents the operation of the rest of the fleet, including successively the dumper trucks, bulldozers, road rollers and other machinery (Figure 5). For this reason, the failure of hydraulic excavators can represent expansive losses in terms of production for the operative process. This situation can be even more dramatic if the works are being executed by only one fleet, where only one excavator is present. Many construction works cannot afford in their budgets the simultaneously work of two excavators, becoming maintenance the key tenet for the project success.

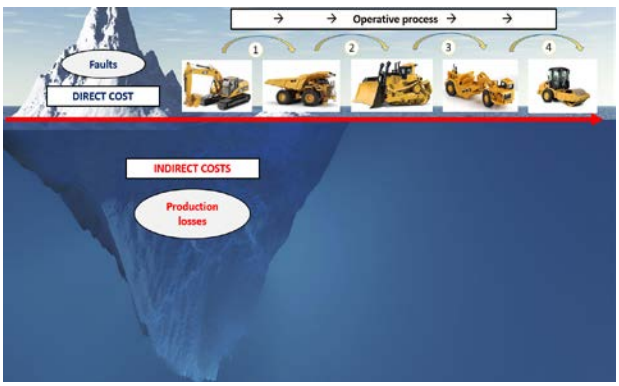

Fig.5: Iceberg graph showing the proportion between direct and indirect costs in a fleet led by a hydraulic excavator.

4.2 Fault severity

Aleatory or stochastic uncertainty due to the faults randomness is always at some point inherent to the variability of the system regardless of how good the maintenance strategy is. However, epistemic or subjective uncertainty arising from the lack of knowledge about the system and its behaviour can be certainly reduced by acquiring knowledge through probability and decision models like the one shown here. One aspect that holds special importance is the risk of suffering a fault with a high degree of severity, because of its huge cost and long time to repair.

The deterministic node incorporated in the influence diagram (Figure 2) with engineers´ criteria for the fault degree of severity regarding the particular damaged elements in the power unit (Table 2) makes it possible to calculate the risk profile for the machine operating time (Figure 6). The risk profile is important for identifying the acceptable level of risk an individual or corporation is able to accept. It is expressed in terms of risk probability including the results of using in the influence diagram the prior probabilities for both the exponential and Weibull model.

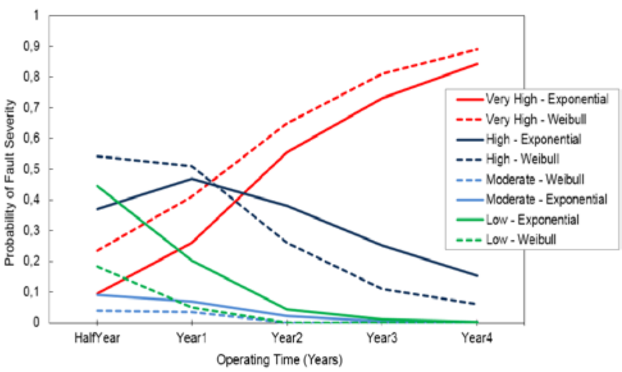

Fig.6: Probability risk profile for the power unit fault severity

As it can be seen in Figure 5, from year 2 the likelihood of having a fault with a very high severity exceeds the 50%. Year 2 can, therefore, set the point for which the risk level determines the maintenance strategy. During the two first years could be implemented an extensive maintenance based on a predictive approach that tries to minimize fault risk levels for the later years. From the third year a preventive maintenance, less exhaustive, can be applied. The aging effect is already present and expensive maintenance approaches could not really stop faults appearance.

This maintenance approach for the hydraulic excavator combines two risk attitudes. First, during the two first years a risk-avoiding attitude toward faults is developed. The predictive maintenance applied is based on high quality with a high cost associated, which is expected to be less than the faults that may occur throughout the life of the machine if it was not applied. Second, from the third year a risk-seeking attitude toward risk is taken. Only the preventive maintenance is going to be undertaken. Faults inevitably are going to happen, so an exhaustive maintenance is not going to suppose too much in relation the fault cost.

To sum up, this approach as a whole tries to constitute a risk-neutral attitude focusing on the successful operation of the machine in the long term taking those actions that are more likely to lead to significant benefit.

5 Conclusions

In this article, a new process for the estimation of the power unit failure in mining excavators was developed using an innovative management perspective. The power unit was divided in three main fault elements and from data of faults collected the last years in different mining excavators throughout its operation life, exponential and Weibull probabilistic models were used in order to obtain the prior fault probabilities for each element. The analysis of the prior probabilities into an influence diagram showed that the Weibull model offers a more accurate representation of the expected direct and indirect costs for the power unit.

A risk profile for the faults severity was calculated proposing an optimized maintenance solution for this machinery. Maintenance strategies should be designed under the assumption of a certain probability model that does not influence decisions. Since the selection of the probability model is carried out at an early stage of the design, one might expect a low impact on the final selection of the best strategy. This paper shows how a misspecification of the probability model can lead to erroneous conclusions since early stages causing expansive economic losses. Different alternatives based on several risk attitudes toward uncertainty can be adopted, where not the one with the highest expected gain can necessarily be the best.

Finally, future work is required to analyse and optimize maintenance strategies in other crucial parts of excavators and other mining and civil machinery, especially those exposed to a high level of wear.

References:

[1] M. Haga, W. Hiroshi, K. Fujishima, Digging control System for hydraulic excavator, *Mechatronics*. Vol. 11, No. 6, 2001, pp. 665-676.

[2] Q. Xiao, Q. Wang, Y. Zhang, Control strategies of power system in hybrid hydraulic excavator, *Automation in Construction*, Vol. 17, No. 4, 2008, pp. 361-367.

[3] L. Ge, L. Quan, X. Zhang, B. Zhao, J. Yang, Efficient improvement and evaluation of electric hydraulic excavator with speed and displacement variable pump, *Energy Conservation and Management*, Vol. 150, No. 15, 2017, pp. 62-71.

[4] N. Sedransk, J. Sedransk, Distinguishing among distributions using data from complex sample designs, *Journal of the American Statistical Association*, Vol. 74, No. 368, 1979, pp. 754-760.

[5] B. de Jonge, W. Klingenberg, R. Teunter, T. Tinga, Optimum maintenance strategy under uncertainty in the lifetime distribution, *Reliability Engineering and Systems Safety*, Vol. 133, 2015, pp. 59-67.

[6] R Core Team, A language and environment for statistical computing, *R Foundation for Statistical Computing*, Vienna, Austria, 2016.

[7] R. A. Howard, The foundations of decision analysis revisited. In Advances in decision analysis: from foundations to applications, ed. W. Edwards, R.F. Miles and D. Von Winterfeldt. Cambridge, UK: Cambridge University Press, 2007.

[8] BayesFusion, GeNIe Modeler, BayesFusion, LLc, Data Analytics, Mathematical Modelling, Decision Support. Pittsburgh, PA, 2017. http://www.bayesfusion.com/

[9] R. D. Shachter, Probabilistic inference and influence diagrams, *Operations Research*, Vol. 36, No. 4, 1988, pp. 589-604.

[10] Z. Pawlak, R. Sowinski, Rough set approach to multi-attribute decision analysis, *European Journal of Operational Research*, Vol. 72, No. 3, 1994, pp. 443-459.

[11] J. von Neumann, O. Morgenstern, Theory of games and economic behaviour, *Princenton, NJ. Princenton University*, 1953.