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MULTI-CRITERIA DECISION TOOL APPLIED TO A SYSTEM RELIABILITY FOR THE PRIORIZATION OF SPARE PARTS.

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ABSTRACT

This paper proposes a method for spare part priorization based on the system reliability behavior. The method considers the values taken by the reliability distribution parameters, as the result of a multi-criteria decision process. The range of values is divided into possible alternatives, which depend on the importance of different criteria. The presented exercise provides a quick view about how different spare part policies can be selected by the effect, not only of the design, installation quality or performed maintenance, but also due to factors that sometimes come from subjective assessments. Hence, the Analytic Hierarchy Process (AHP) includes both qualitative and quantitative criteria in the priorization scheme. The presented method is intended to be a starting point for the analysis of external factors that make an important influence on the decision–making of complex industrial assets, with high amounts of data, system configurations, and maintenance inputs, which will be analyzed in future researches with the support of a tailored software application.

1 INTRODUCTION

System reliability depends, mainly, on its design and installation quality. In addition to this, the reliability conservation will depend of course on the maintenance to be performed. Normally, these issues are analyzed from the point of view of a standard utilization of physical assets, under normal or controlled environments. However, external factors (as the usage profile) may affect the better or worse reliability conservation and, as a consequence, different maintenance plan can be tailored. Additionally, the current complexity of equipment provides difficulties for modeling the reliability behavior of a system, as far as components are generally a mix of taxonomies with different origins (electrical, mechanical, hydraulic, pneumatic etc.).

The objective of this brief study is to link some production criteria with those possible parameter values given for the system reliability. In order to illustrate this goal, an example is shown considering a Weibull distribution (as far as it is one of the most extended statistical distribution for modeling system reliability), and taking different values for its parameters. In order to simplify this sensitivity analysis, the present paper will consider failure rates intervals as well as different values for the shape parameter. Actually, the proposed methodology starts from a multi-criteria analysis with the target of selecting those parameter values that better match with the circumstances around the system.

The result will allow the analysis of the system reliability under specific parameter values. Finally, the maintenance or asset manager will be able to take a decision in aspects related to spare parts management, being able to be (for instance) more or less conservative or risky depending on the importance or weights considered during the multi-criteria decision process. With that purpose, this paper will start with a brief literature review on reliability linked to spare parts management. Afterwards, the proposed methodology for spare parts priorization is depicted. Then, with the support of a simple example, the study will approach the reliability uncertainty considering different alternatives for failure rate and shape parameter. The obtained results are shown and discussed in the following section, providing different points of view for the sensitivity analysis and how the selected parameter values may depend on diverse, external and sometimes subjective factors. Finally, there are some conclusions at the end of the paper, summarizing the main lines of this research.

2 BRIEF LITERATURE REVIEW

2.1 *On the Reliability Assessment*

Currently, different alternatives exist for the individual and systemic logical-functional representation of processes (Viveros et Al. 2011). The Reliability Block Diagram RBD methodology permits the representation of a system as a network of organized components, identify in terms of operation continuity, the contribution and effect of each on the system. This technique is better adjusted to non-repairable component systems and when the order of failure occurrence is not important. In addition to this, a complexity recognized in the productive processes of the mining industry is the large amount of equipment and systems, so that the industry prioritizes the use of functional tools with practical implementation and already proven in different plants and mining processes (Viveros et Al. 2011).

The RBD analysis methodology (Rausand & Hoyland, 2003; Guo & Yang, 2007), is a widely used technique in the mining sector, due to its adaptability to represent complex provisions and environments with large amounts of equipment, where they look for ways to simplify the reliability analysis through the use of block diagrams under systematic configurations in series, parallel or other more complex configurations (Guo & Yang, 2007). However, when working with reparable component systems and when the order in which the failures are represented is important, the Markov method is generally the most convenient (Rausand & Hoyland, 2003). For the calculation of Reliability of the subsystem in parallel or full redundancy, we use:

$$R_{sub}(t) = 1 - \prod (1 - R_i(t)) \tag{1}$$

Where $R_i(t)$ represents the individual reliability of the equipment. The k-out-of-n system structure is a type of structure in which system can operate, only if at least k of the n components are correctly working. For the reliability analysis, the formulation used is according to the probability of the Event Space Method (Lisnianski, 2007), where for a redundant system n over j, the reliability is represented by:

$$R_{sub}(t) = \sum_{j=m}^{n} \binom{n}{j} R^j * (1 - R_j)^{n-j} \tag{2}$$

However, this formulation assumes that the reliability of n equipments are similar, so none can be generalized to this case since the equipments have different adjustment parameters, and therefore its behavior in terms of reliability is different. For this reason, as an example: for a Subsystem, 3-out-of- 2, the formula will be:

$$\mathrm{R_{Sub}}(\mathrm{t}) = \prod_{i=1}^{3} R_i + (1 - R_3) * R_1 * R_2 + (1 - R_2) * R_1 * R_3 + (1 - R_3) * R_1 * R_2 \tag{3}$$

For a load sharing subsystem, example: for 60% and 40% distribution, the reliability formulation is:

$$\mathrm{R_{Sub}}(\mathrm{t}) = \sum_{i=1}^{n} R_i(t) * I_i + (1 - \sum_{i=1}^{n} I_i) * \prod_{i=1}^{n} R_i(t) \tag{4}$$

According to the last formulation, $R_i(t)$ represents the individual reliability of each equipment, and I_i is the impact on production system as a consequence of the failure of the equipment i. The second part of the equation (4) [$(1-\sum_{i=1}^{n} I_i) * \prod_{i=1}^{n} R_i(t)$], has importance when the capacity of the system, represented by the sum of the individual capacities of the equipment, is greater than 100% of demand, it means that exist a load sharing structure with overcapacity. Finally, the reliability of overall system, represented by a serial structure, would be equivalent to:

$$R_{Sub}(t) = \prod_{i=1}^{n} R_i(t) \qquad (5)$$

Generally, if the reliability of a system needs to be improved, then efforts should first be concentrated on improving the reliability of the component that has the largest effect on reliability (Macchi et Al. 2012).

2.2 *Link to the Spare Parts Management*

The literature regarding reliability analysis usually deals with system features like "Ratio of system failure", "Mean Time Between Failure" (MTBF), or "Mean Down Time" (Rausand and Høyland, 2003; American Institute of Chemical Engineers, 1989).On the other hand, the bibliography about Spare Parts Management covers a wide range of topics: stocking strategies (Molenaers et Al. 2012), inventory control (Kennedy et al. 2002), priorization based on demand (Syntetos et al. (2009), realistic classification approaches (Braglia et al. 2004), among many others. In order to link the reliability analysis with the system units (those units that constitute the industrial assets), the following chart (Table 1) shows the expressions in terms from the components themselves.

Formulas	Two subsystems in Series	Two subsystems in Parallel
System Failure Rate	$\lambda_{series} = \lambda_1 + \lambda_2$	$\lambda_{paralllel} = \lambda_1 \cdot \lambda_2 \cdot (MDT_1 + MDT_2)$
System MTBF	$MTBF_{series} = (MTBF_1 \cdot MTBF_2) / (MTBF_1 + MTBF_2)$	$MTBF_{parallel} = (MTBF_1 \cdot MTBF_2) / (MDT_1 + MDT_2)$
System Mean Down Time (MDT)	$MDT_{series} = (MTBF_1 \cdot MDT_2 + MTBF_2 \cdot MDT_1) / (MTBF_1 + MTBF_2)$	$MDT_{parallel} = (MDT_1 \cdot MDT_2) / (MDT_1 + MDT_2)$

Table 1. Summary chart of formulas

The conventional formulas mentioned above are sometimes not used in cases of hybrid configurations. Other methods such as a probabilistic formulation (Henley and Kumamoto, 1992) are usually applied for these hybrid cases. Nevertheless, using the a.m. conventional formulas, one can observe from the quantitative assessment of these parameters (González-Prida et Al. 2009), those subunits or components which can be critical in the functioning of the entire system (Crespo and Iung, 2007). The obtained result allows tailoring for example the possibility of a preliminary list of recommended spares (González-Prida et Al. 2010). This kind of analysis are easy to implement during the design phase, and useful once the system is launched to the market and starts working. Once the system performance is known, it is possible to apply a similar analysis with real data about the system behaviour, making easier and more realistic the decision taking for future batches of spare parts. Other interesting references in this field are (Barberá et Al. 2010), (Vintr 2007) or (González-Prida and Crespo, 2010).

2.3 *Risk analysis and probability of failure*

The common definition of risk (associated with hazard) is the probability that a hazard will occur and the (usually negative) consequences of that hazard. In essence, it comes down to the following expression (the most frequently used definition in risk analysis) ISO 31000, 2002, where R is the risk, P_{fi} is the probability of failure and C_{fi} represent the consequences of the unwanted event.

$$Risk = \sum_{i=1} P_{f_i} * C_{f_i} \tag{6}$$

According to Kaplan and Garrick, risk consists of three components; (1) the scenario, (2) the probability of the scenario and (3) the consequences of the scenario. Kaplan and Garrick, 1981. Also suggests that one has to take all hazards into account, which can be accomplished by summing up all possible hazards (scenarios) with their consequences for a certain activity. Particularly for the calculation of probability, we refer to the reliability of the equipment, which depend directly on the parameters of life of its distribution function. The changing and evolution of life parameters affect directly on the life expectancy (MTBF) and consequently in the number of changes (parts) in a finite time period.

For example, decision makers have to consider that the number of events equals the number of failures allowable for the system to continue running during the analysis period t, which should be less than or equal to the number of parts available. It is possible to obtain all the probabilities for the success or failures scenarios. Therefore, the results are probabilistic for discrete scenarios, so that the maximum allowable failures and the number of available spare parts are integer numbers. In the other hand, the consequence depend of the attributes or criteria considered, according to the significance of business itself.

3 PRIORIZATION OF SPARE PARTS

Despite the possible procedure of ranking the maintainable items according just to their reliability, a more complex replacement model for spare parts is developed by Molenaers et Al. 2012. Such a model considers other criticality criteria like:

- Frequency of a failure
- Possible consequences of a failure
- Probability of item failure
- Replenishment time
- Number of potential suppliers
- Availability of technical specifications
- Maintenance type

Different criteria can also be observed in case studies like Gonzalez-Prida et Al. 2011, where the AHP is implemented considering criteria like: availability of extra stock, repair/supply cost and terms, and (in that scenario), the number of assets under warranty and the number still to deliver. As introduced in the first section, the objective now is to link some of the above mentioned criteria (or choosing new ones) with those possible parameter values given for the reliability models. Gajpal et al. (1994) and Braglia et al. (2004) adopted the AHP approach for spare parts classification based on criticality. The proposed methodology considers the possible parameter values or intervals as alternatives in a multi-criteria decision tool (Table 2).

		Characteristics	
Alternatives	Parameters	Working Conditions	Items Type
A	Lambda Max. & Beta Min.	Severe	Mechanical
B	Lambda Max. & Beta Max.	Severe	Electrical
C	Lambda Min. & Beta Min.	Soft	Mechanical
D	Lambda Min. & Beta Max.	Soft	Electrical

Table 2. Example of alternatives for the sensitivity analysis

In other words, the novelty here is to consider for the reliability modeling, those factors that can make the parameters to take different values. These factors will change from the point of view of technical requirements, facilities and boundary conditions, etc. Spare parts are considered critical (Huiskonen 2001) for a production process (from the point of view of the consequences for an industrial plant) or functional control (from the point of view of industrial assets fleets). Therefore, many attributes can be taken into account as criteria for the hierarchy process. Based on their significance to the business itself, some examples for criteria are presented in Table 3.

Criticality criteria	Description
Production requirement	Expected quantity of products obtained in a defined term and under specific quality standard by the industrial process of transforming tangible (materials) and intangible (knowledge) inputs into goods or services.
Installation environment	Conditions that surrounds an assembly of systems. Under such conditions, the whole machinery should run and work properly.
System availability	Characteristic of an industrial resource, which is committable, operable, or usable on demand to perform its required function. This characteristic extends the definition to elements such as quantity and proximity of spares, tools and manpower to the resource itself.

Table 3. Example of criticality criteria

Once known the criteria and alternatives (Figure 1), maintenance and assets managers may proceed to calculate the relative importance or weight, according to their judgements, which are transformed into mathematical matrices.

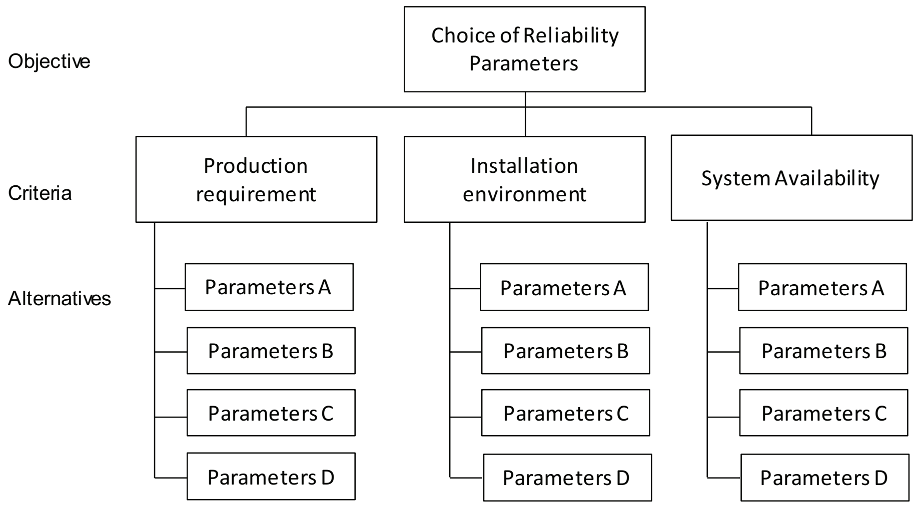

Figure 1. Hierarchy process

To sum up, the proposed method considers then the following steps:

i. Definition of statistical distribution in order to model the system reliability.
ii. Definition of plausible intervals and ranges for the reliability parameters.
iii. Definition of alternatives according to parameter values and intervals.
iv. Definition of criticality criteria for production process or functional control.
v. Calculation with the AHP procedure.
vi. Implementation of the selected alternative to the statistical distribution.
vii. Obtaining a ranking of maintainable items according to their reliability.
viii. Selection of spares (for example, by Pareto principle, or economic considerations)

4 APPROACHES TO THE RELIABILITY UNCERTAINTY

4.1 *Scenario and prior conditions*

In order to analyse the system reliability considering a specific failure rate interval as well as different values for the shape parameter, we will consider a very simple system constituted by four components or maintainable items. The configuration of the system functional blocks (ISO/DIS 14224), as we can see in Figure 2, will be two components (A and B) in series, plus another two components (C and D) in parallel. The intention here is to obtain the system reliability R(t), as a function of the component characteristics. In other words, applying the formulas from Table 1, we obtain for the whole system, the following expressions for system failure rate (7), and system MTBF (8).

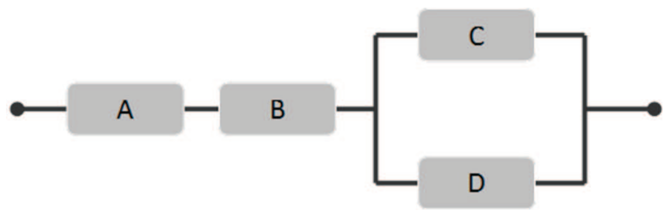

Figure 2. Block diagram example

$$\lambda_1 = \lambda_A + \lambda_B + \lambda_C \cdot \lambda_D \cdot (MDT_C + MDT_D) \tag{7}$$

$$MTBF_1 = \left[\frac{MTBF_A \cdot MTBF_B}{MTBF_A + MTBF_B} \cdot \frac{MTBF_C \cdot MTBF_D}{MDT_C + MDT_D}\right] \div \left[\frac{MTBF_A \cdot MTBF_B}{MTBF_A + MTBF_B} + \frac{MTBF_C \cdot MTBF_D}{MDT_C + MDT_D}\right] \tag{8}$$

Based on the above formulation and considering a constant failure rate for the system life cycle as well as a Weibull distribution as a model for the reliability behavior over time (9), it is possible to obtain reliability values R(t) (Meeker and Escobar, 1999) for the complete system.

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{9}$$

In the expression for R(t), for each equipment:

- t: time
- β: shape parameter
- η: characteristic life

Particularizing to our example, we will analyze the system evolution during 1 year (twelve months). Therefore, t=[1, 12]; the shape parameter will assume a Weibull Distribution with β=0.5, till an Exponential Distribution (β=1); and finally, the characteristic life will be considered as η = MTBF $\cdot$ 10^{-6}, which depends on the values taken for the failure rate. Basically, the assumed data for sensitivity analysis will be those ones included in the following chart (Table 4).

The assumed values for β consider the case when the elements are electrical items, then β=1 (the Weibull expression refers then to an Exponential distribution); or the case when the elements are mechanical items, then β=0.5 (Lawless J.F.). The physical explanation is that mechanical items are usually deteriorating overtime faster than the electrical ones (Parra et Al. 2006). In other words, the goal with the different values for shape parameter is to consider pure electrical components or pure mechanical components, as far as the curve trend in both cases are different depending if the components are just electrical or mechanical. Therefore, the shape parameter for mechanical components should be lower than the shape parameter for the electrical items.

Parameter	Min	Max
Beta	0.500	1.000
Lambda A	125.000	225.000
Lambda B	100.000	200.000
Lambda C	5.000	20.000
Lambda D	10.000	15.000

Table 4. Assumed data for the sensitivity example

Similarly, the values of λ are higher when the system is considered to be used under severe conditions (higher trend to the failure), or lower when the usage conditions are even softer than the standard conditions. In other words, the goal with a failure rate interval is to consider different usage profiles or environmental severities. Values for failure rates can be obtained from data bases as Oreda or Faradip (Sintef, 2002; Smith, 2001).

4.2 *Calculations*

Considering the assumed values for Lambda (failure rate) and Beta (shape parameter), it is possible to calculate the system reliability R(t) according to different combinations of the commented values. In our case, we will take into account just the four extreme cases as alternatives for our multi-criteria decision process:

A. Lambda Max. & Beta = 0,5
B. Lambda Max. & Beta = 1
C. Lambda Min. & Beta = 0,5
D. Lambda Min. & Beta = 1

Providing the calculations just for alternative A, the values for R(t) is shown in the following chart (Table 5):

t (month)	Item A	Item B	Item C	Item D	System
1	0.6642	0.6799	0.8852	0.8997	0.5699
2	0.5687	0.5873	0.8451	0.8644	0.4604
3	0.4980	0.5183	0.8123	0.8353	0.3836
4	0.4471	0.4682	0.7866	0.8123	0.3308
5	0.4054	0.4268	0.7640	0.7920	0.2891
6	0.3721	0.3937	0.7447	0.7747	0.2570
7	0.3430	0.3647	0.7269	0.7586	0.2298

t (month)	Item A	Item B	Item C	Item D	System
8	0.3181	0.3396	0.7107	0.7440	0.2071
9	0.2970	0.3183	0.6963	0.7309	0.1885
10	0.2777	0.2988	0.6825	0.7183	0.1719
11	0.2611	0.2819	0.6701	0.7070	0.1579
12	0.2456	0.2662	0.6580	0.6959	0.1452

Table 5. Reliability values considering λ max. and β=0,5

Graphically, the above mentioned chart can be represented with the curves shown in Figure 3. In the same way, it is possible to obtain the values for R(t) in alternatives B, C and D. Nevertheless, according to the proposed method, the alternative to be implemented to analyze the reliability evolution of the system should be the one obtained as a result of the AHP process. Such a process is not here included as far as the procedure is quite well known and does not provide a significant novelty to the current research.

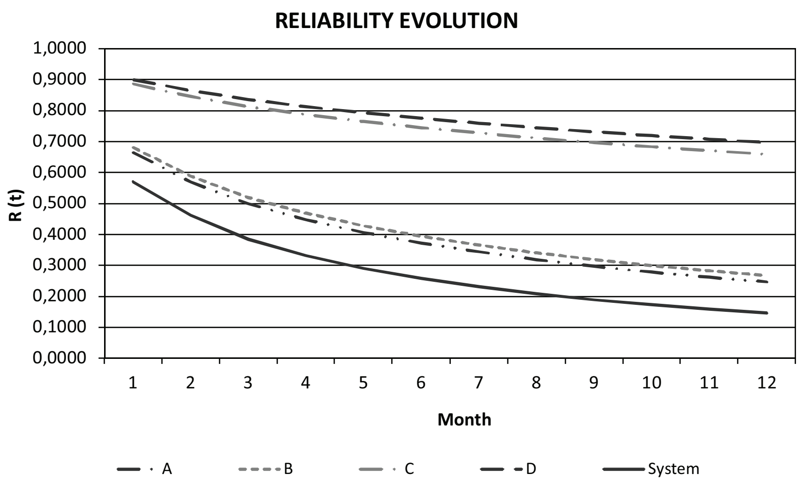

Figure 3. Graphical representation of alternative A

Another interesting quantitative proposal to analyze this phenomenon is according to (Ramirez-Marquez et Al. 2006) and (Barabady and Kumar, 2008), where the reliability importance, I, of component i in a system of n components is given by:

$$I(i) = \frac{dR_s(t)}{dR_i(t)} \tag{9}$$

Where $R_s(t)$ is the system reliability, and $R_i(t)$ is the component reliability.

4.3 ***Results***

From these values, it is possible to obtain for each alternative a ranking of “items reliability”. This ranking can be a helpful tool in order to decide which components should be prioritized in comparison to the rest, in order to draw up a list of recommended spares. Of course, this example has not consider the implementation of the AHP decision tool, or the monetary value of the spare parts. Nevertheless, it is possible to illustrate the curves for the system reliability behavior, according to each alternative. This representation is shown in Figure 4.

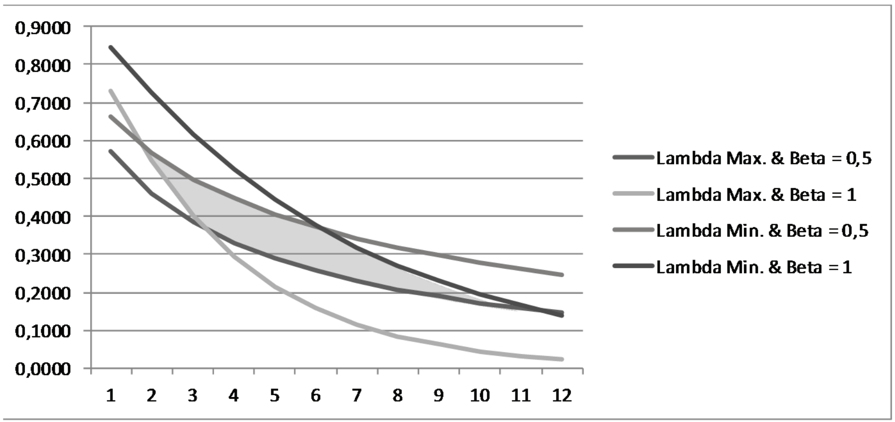

Figure 4. System reliability behavior according to each case

As already commented, if the four items are the possible spare parts they can be prioritized according to their unreliability. Therefore, considering each alternative, the unreliability ranking is shown in the following chart (Table 6).

RANKING	Item A	Item B	Item C	Item D
Lambda Max. & Beta = 0.5	4	3	2	1
Lambda Max. & Beta = 1	4	3	2	1
Lambda Min. & Beta = 0.5	4	3	1	2
Lambda Min. & Beta = 1	4	3	1	2

Table 6. Unreliability ranking of items acc. to each alternative

5 DISCUSSION AND FUTURE APPLICATIONS

With this easy example, we observe that:

a) Depending on the alternative considered, the need of a component as spare part varies.
b) The value of β also affect to the ranking of spare parts need (although it is not perceptible with the values of this example).
c) The exercise has assumed a pure mechanical case (all β=0.5) and a pure electrical case (all β=1). However, items in the reality are mixed, interacting electromechanical components (or hydraulic, pneumatic, etc.), which may present a different shape parameter.
d) The most conservative position would be the scenario that assumes the worst system performance (higher failure rate).
e) On the contrary, the most probable situation would be that one whose parameters take values adjusted to a more realistic behavior. That means, λ and β would take values within the range [min, max], but not necessarily in the extreme (as assumed by this example).

Therefore, the most probable situation does not have to coincide with the most conservative one. As a consequence, future applications that this study may provider are:

- If we foresee the system usage profile, it is possible provide to the end user a tailor-made list of recommended spare parts.

- Similarly to the spare parts, maintenance plan may also vary according to the severity of use or working environment. The possible changes can affect the task frequency, and obviously the order of application in the maintenance schedule.

The outlined example can be implemented in a more complex way (i.e., with more number of subsystems and levels for example to reach the maintainable items; or considering different statistical distributions with diverse parameters and rates). With that target, the next step will be the implementation of the proposed methodology, including the AHP calculation, in a software for the processing of a high amount of data, values and system configurations, which allow the performance of simulations, histograms etc. This future study will consider as decision variables not only the Reliability R(t), but also Maintainability, Cost, Production, Availability, Usage etc.

The effectiveness of production processes and the equipment that are part of them is generally measured according to the results of reliability and availability indicators, as well as through the economic analysis of its life cycle. In addition to this, the OEE indicator allows for the measurement of productive efficiency using the control parameters as a basis for calculating fundamentals in industrial production: availability, efficiency and quality. The productive processes in the mining industry (future development) have, as an additional complexity, a large amount of equipment and systems, which make the systematic analysis of the plant more difficult. Because of this, different analysis methodologies have been developed, like the last explained RBD methodology, widely used in the mining sector for its adaptability of representation in complex arrangements and environments with large amounts of equipment, where they look to simplify the reliability analysis through the use of diagram blocks under systemic configurations mainly in serial and parallel All decision parameters are actually the output of a series of qualitative or quantitative factors. These factors may be for instance the required level of service, the investor profile, the needed workload etc. obtaining as a result solutions packages which will be dependent on the system boundary conditions.

6 CONCLUSION

This paper suggests a methodology to select spare parts for an assumed system. The proposed method provides to the reader an easy view about the effect over the system maintenance, not only the design or installation quality, but also the consideration of external (and sometimes subjective) factors. The exercise considers different shape parameters and intervals for the failure rates. The failure rate has been here considered as a constant during the life cycle of the system. Nevertheless, all these parameters should be assessed based on different factors as a result of a multi-criteria decision tool. The presented study implies how usage profile and/or severity of the working conditions may affect to the decision of required spares, but also task frequency, or other aspects of the maintenance policies. Moreover, achieving a good level of reliability, especially in the critical assets, requires appropriate analysis and prioritization in the allocation of resources and adequate allocation of maintenance policies according to the criticality of maintainable each element. Therefore, a method for convenient and practical hierarchical becomes an important tool for the success of the maintenance function and, in some cases, its complement methodologies for auditing the resources allocation of critical maintenance activities. In conclusion we can say that is necessary to have this type of tool that dynamically, can re-establish procurement policies spares and adjust to changing business conditions the values of R (t) of our equipment.

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