



DATA-DRIVEN RELIABILITY OF ELECTRONIC EQUIPMENT

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Abstract: Reliability is important especially for military, medical and other professional equipment. Reliability management and/or prognostic reliability calculation have always been data-driven. The definition of data-driven concept, then definition of reliability is briefly discussed, and after that the impact of uncertain data on prognostic reliability calculation and also reliability and availability of data is discussed in this paper.

Keywords: data-driven, reliability, availability, data, equation.

1. INTRODUCTION

Reliability as theory and practice appeared at fifties of the last century. First it was applied to hardware, then software and human. Reliability is still actual and very important in nowadays [1].

Reliability has always been data-driven [2]. Without good data prognostic reliability is useless, in spite of good reliability model. So, input data in reliability model and in decision making system in reliability management are of crucial importance.

How to obtain good data is big problem. We can rarely get such data from producers of components or devices (electronic, mechanical) and/or software. Up to nineties of last century we were able to use data about failure rate of electronic elements from well known military handbook MIL-HDBH-217 [3]. But these are data from the past, and the last version of that handbook is from 1995, so that data are obsolete [1]. And that data is statistical, and reliability (in other word probability) which we calculate based on this data is valid only with a certain probability. We can use some data from other sources but they also usually are not up to date.

So, we can put the question: calculate reliability or not to calculate? From this author experience (of almost 30 years of teaching (talking to students that input data is the biggest problem in reliability calculation) and 40 years of practice in reliability calculation of electronic equipment) it is better do the calculation even based on an obsolete data, specially at the beginning of designing device or system, because it can help to chose better solution (alternative) from the point of view of reliability.

Of course, when we need to decide if such devices, software or system satisfies certain required reliability requirements, then we can not rely on obsolete or uncertain data.

In [4] is concluded that the problem is how to cope with large amounts of data on the one hand, and with very small amounts of data on the other hand. Both of these can be the case in reliability and maintenance, and more often we have problem with not enough or no any data.

First the definition of data-driven concept, then definition of reliability is briefly discussed, and after that the impact of uncertain data on prognostic reliability calculation and reliability and availability of data is discussed.

2. DEFINITION OF DATA-DRIVEN

Being data-driven means that all decisions and processes are based on the data. This is most evident in the field of big data [2, 5]. It is in connection with data science, data mining, etc. The term data-driven is used in many fields, also in reliability.

Being based on data means using data, and using data means at least collecting and analysing data. And this implies using some kind of communication. To achieve this, we as a person or organisation use technology (different devices, networks, software, Internet of Things, etc.), and anything of these can fail. Of course, we want to avoid failures and resolve them if they happen, and this is the task of reliability.

Data-driven as a term describes a decision-making process which involves collecting data, extracting patterns and facts from that data, and utilizing those facts to make inferences that influence decision-making [6].

Making decisions, is a fundamental component of business and personal management. Good decisions lead to success while poor decisions lead to loss or failure. And this depends of data.

Every organisation today aims to be data-driven. Data-driven decision making is the process of making organizational decisions based on actual data rather than intuition or observation alone. This is the case in reliability also.

Before analysing impact of data on reliability, we will, in short, explain the definition of reliability.

3. DEFINITION OF RELIABILITY

Reliability is very important not only in military and professional products. Reliability in nowadays also plays a crucial role for safety and adoption of driverless cars.

Reliability is the probability that a device will meet intended standards of performance and deliver the desired results within a specified period of time under specified (environmental) conditions [2].

4. IMPACT OF DATA ON RELIABILITY

As we stated before, reliability has always been data-driven (if being data-driven means that all decisions and processes are based on the data), and valid and relevant data always has been main problem. It only depends if that data is historical (from past experience on failures) or data gathered from new device for which we calculate reliability. Of course, data gathered from new device for which we calculate reliability are more valuable than data from the past experience, because data from past are from different devices and older components, if we are using data from handbooks, for example MIL-HDBK 217. Data about failure rate of new components are rare available from producers.

In MIL-HDBK-217E (1986) is stated that „Considerable effort is required to generate sufficient data on a part class to report a statistically valid reliability figure for that class. Casual data gathering on a part class occasionally accumulates data more slowly than the advance of technology in that class; consequently, a valid level of data is never attained.“ [3].

In MIL-HDBK-217F (1991) is stated “The first limitation is that the failure rate models are point estimates which are based on available data.”

Obviously, there are problems to gather sufficient and good data, in spite of our effort. The problem is not only insufficient data, but also accuracy of that data.

We will discuss impact of data on reliability from several aspects: accuracy, availability, and up to date of data, experience, culture in organisation, and etc. Data also are the base for reliability test developing.

Reliability calculation (or better to say estimation) is always predictive (prognostic) because we want to know what will happen in the future, for example what is probability that that device will not fail after a certain time of using. First let us see how error or accuracy in input data in simple reliability model (reliability block diagram, RBD) can affect results for prognostic reliability calculation. In so called Parts Count reliability calculation which is implemented in MIL-HDBK-217, serial configuration RBD model is used (Fig. 1.) [7].

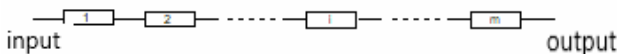


Figure 1. Serial RBD model

Fig. 2. shows reliability of serial RBD model R_s as function of reliability of element (all elements are with the same reliability R) and number of these elements m . From Fig. 2. we can see that error in input data (if we consider difference in R as an error in input data) for reliability of one element has bigger impact on reliability when system has more components, and this is usually the case. For example if we have serial RBD with 5 elements, and reliability of each element is $R=0,8$, than error of

$\pm 10\%$ will produce error in reliability of system R_s of + 61% and - 41%.

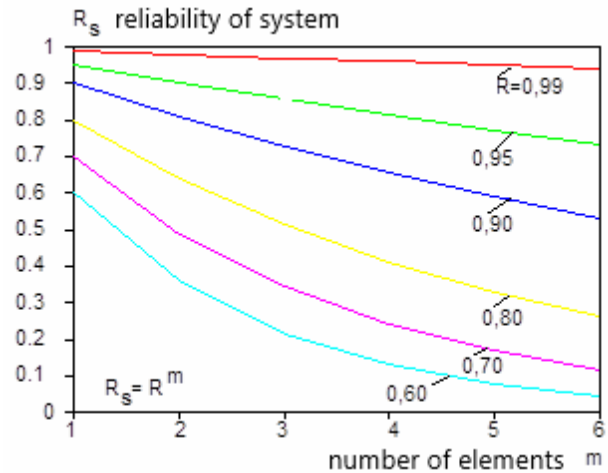


Figure 2. Reliability of serial RBD model

In Fig 3. is shown parallel RBD model of a system. Fig. 4. shows reliability of parallel RBD model as function of reliability of element (all elements are with the same reliability) and number of these elements n . From Fig. 4. we can see that error in input data for one element has smaller impact on reliability when system has more components, but in this case system is more costly. Adding second element with mean time to failure (MTTF) will increase mean time to failure of system (MTTF_s) for 50%, adding third element for 33%, adding fourth element for 25%, and this is obvious from equation [7]

$$MTTF_s = MTTF \left(1 + \frac{1}{2} + \dots + \frac{1}{n} \right) \quad (1)$$

So, adding more elements in parallel to increase reliability will more increase cost then reliability. Reliability and cost are mutually dependent. Higher reliability means higher cost, but cost for maintenance will be lower.

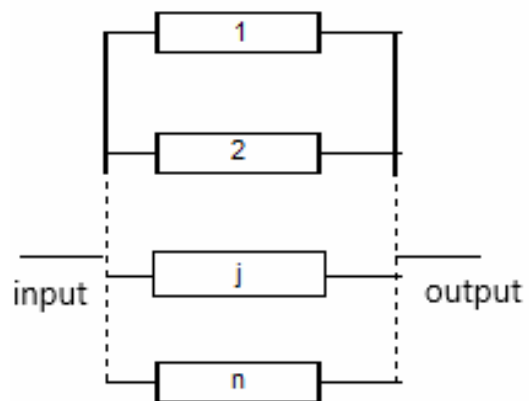


Figure 3. Parallel RBD model

Experience of this author has shown that the calculated prognostic MTBF of electronic equipment, using MIL-HDBK-217, should be at least or about twice of the required MTBF in order to have operational (actual, correct) MTBF equal to required (original) MTBF and that was applied as a rule when Parts Count reliability calculation has been made [7].

This is not only experience of this author that the problem is also in inadequate input data of electronic elements and inadequate estimation of this input data in the calculation of reliability [7].

And another problem with data is when we have small number of produced devices, so we have not enough data.

Another problem is with devices with very high required reliability: In this case we will get real data after a long time after entering this devices in usage.

Availability of good data is very big problem, specially today, when technology is changing very fast, and some components are very reliable (but we don't know how much) and do not have timely and accurate data about its failure rate, in other words reliability.

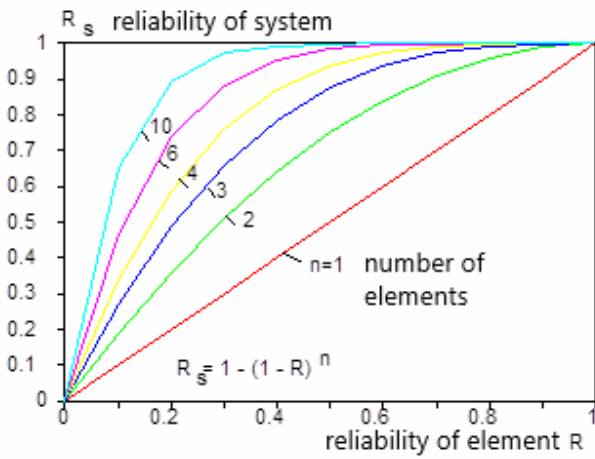


Figure 4. Reliability of parallel RBD model

One solution for problem when there is not enough relevant data is seen in so called Physics of failure, but it is applicable in wear area of failure rate. But in Physics of failure we again have problem not only with relevant data but also of knowledge of different processes in component material [1].

Besides of input data in models for reliability calculation, data from reliability analysis of a system or device can tell us more. For example, in [8] The Boeing 787 Dreamliner reliability is analysed using data-driven approach. From the various documents and trends they concluded that Boeing did not adopt an effective Reliability Program Plan, where best practice tasks are implemented to produce reliable products. Boeing opted to widen its supplier base and reduce costs by including manufacturers who were new to the aircraft development industry. The events that led to delays during manufacturing and failures during operation are a testament to Boeing's flawed practices.

Just as an example let us see what they concluded (learned) from that data. Lessons learned:

- Short development cycle and highly complex supply chains,
- Lack of accurate and timely information sharing,
- Lack of relevant data,
- Lack of valid testing on innovative technologies,
- Difficulty in fault detection,
- Lack of balance between autonomy and oversight.

Furthermore, these deficiencies are seldom independent of each other and can have a compounding effect on product reliability.

Data quality is of course only one problem in reliability. In [9] it is stated that there is no standard method for creating hardware reliability prediction, so predictions vary widely in terms of methodological rigor, data quality, extent of analysis, and uncertainty, and documentation of the prediction process employed is often not presented. Because of that IEEE has created a standard IEEE Std.1413 (Standard Framework for the Reliability Prediction of Hardware) in 2009.

Gathering good data is in connection with people and organization culture. The most important part of the development of a reliability program in the organization is to have a culture of reliability. It is extremely important that everyone who is involved in the creation of products, from top to down, realize that a good reliability program is necessary for the success of the organization [7, 10].

The reliability effort produces and uses a different amount of information and data.

One possible solution when there is not enough relevant data and we can not derive analytical reliability model, is simulation [11]. As an example of not so complex problem is illustrated in [12].

Reliability is connected with maintainability. Reliability and maintainability are important factors in the total cost of equipment. An increase in maintainability can lead to reduction in operation and support costs. For example, a more maintainable product lowers maintenance time and operating costs. Furthermore, more efficient maintenance means a faster return to operation or service, decreasing downtime [13]. Again, we need good and timely data.

5. RELIABILITY AND AVAILABILITY OF DATA

We can discuss also reliability of data, and availability of data. In order to build trust in data, it's critical that it's reliable, which means that it's complete and accurate.

Data reliability means that data is complete and accurate, and it is a crucial foundation for building data trust across the any organization. Ensuring data reliability is one of the main objectives of data integrity initiatives, which are also used to maintain data security, data quality, and regulatory compliance [14, 2].

Reliability leaders need reliable data to make reliable decisions. So, in data-driven reliability, data reliability is of crucial importance. Data reliability is not the same as data validity. The reliability of the data is based on the validity, completeness, and uniqueness of the data [2].

In reliability, nowadays we are facing not only with lack of good data, but with lack of any data. People dealing with reliability calculation can see that obviously.

If we using internet of things (IoT) to gathered data, because of unreliable IoT, data can be missing, incomplete and/or corrupted [2].

Data for maintainability are usually gathered from sensors or IoT, if these are not reliable, data can also be unreliable. Unreliable IoT can produce unreliable data as input in decision-making system, so decision can be wrong.

Similar situation can be with artificial intelligence incorporated in decision-making system. Can artificial intelligence recognize bad data, or we will believe in decision get in such way.

6. RELIABILITY EQUATION

Because data-driven reliability system includes hardware, software, sometimes humans, and data, we suggest assessing the reliability of the data-driven reliability system by changing the equation from the [2, 15, 16] to next:

$$R_S(t) = R_{HW}(t)R_{SF}(t)R_H(t)R_D(t) \quad (2)$$

where R_{HW} , R_{SF} , R_H and R_D are reliability of hardware, software, human and data subsystem, respectively.

7. CONCLUSION

Reliability is still very important. Reliability has always been data-driven and valid and relevant data always has been main problem. Without good data prognostic reliability is useless, inspite of good reliability model. It can be the case with maintainability also.

In reliability calculation we usually have bigger problem with not enough relevant data than with large amounts of data. The problem is not only insufficient data, but also accuracy of that data.

In reliability calculation usually data from MIL-HDBK-217 are used, and these are data form the past, usually obsolete. Up to date data of failure rate of elements are rarely available.

References

- [1] POKORNI S.: *Problems of reliability prediction of electronic equipment*. 6th International Scientific Conference on Defensive Technologies OTEH 2014, 9-10 October 2014, pp 835-838
- [2] POKORNI, S.: *The Reliability of Data-driven Internet of Things Systems*, Annals of Spiru Haret University. Economic Series, 2021, 21(4) 43-52, doi: <https://doi.org/10.26458/2141>, <https://drive.google.com/file/d/18medRDVNqEJzqbeORQUkobRgItBnu2Xu/view>
- [3] MILITARY HANDBOOK, Reliability Prediction of Electronic Equipment, Department of Defense, Washington DC, MIL-HDBK-217E, 1986.
- [4] POKORNI S.: *Current State of the Artificial Intelligence in Reliability and Maintainability*, Vojnotehnički glasnik/Military Technical Courier, 2021, Vol. 69, Issue 3, pp. 578-593, DOI: <https://doi.org/10.5937/vojtehg69-30434>, ISSN 0042-8469, UDC 623 + 355/359
- [5] Techopedia. Available at <https://www.techopedia.com/definition/18687/data-driven>
- [6] Northeastern University. <https://www.northeastern.edu/graduate/blog/data-driven-decision-making/>
- [7] POKORNI S.: *Reliability and maintenance of technical systems*. Military academy, Belgrade, 2004. (In Serbian)
- [8] PANDIAN G., PECHT M., ZIO E., HODKIEWICZ M. Data-driven reliability analysis of Boeing 787 Dreamliner. Chinese Journal of Aeronautics (on line) Available at: <https://www.sciencedirect.com/science/article/pii/S1000936120300546>
- [9] ELEARTH G. J., PECHT M., "IEEE 1413: A Standard for Reliability Predictions", *IEEE Transactions on Reliability*, Vol. 61, No. 1, March 2012, pp. 125-129
- [10] POKORNI S.: *Reliability prediction of electronic equipment: Problems and experience*. 7th International Scientific Conference on Defensive Technologies OTEH 2016, Belgrade, 6-7 October 2016
- [11] POKORNI S.: *Reliability estimation of a complex communication network by simulation*. 19th Telecommunications Forum (TELFOR) 2011. Proceedings of Papers, pp 226-229
- [12] POKORNI S., RAMOVIĆ R.: *Reliability and availability of telecommunication system of four ring connected stations*. Communications in Dependability and Quality Management, An International Journal
- [13] Data-Driven Aerospace Engineering: Reframing the Industry with Machine Learning <https://arc.aiaa.org/doi/10.2514/1.J060131> (on line): 20 Jul 2021 <https://doi.org/10.2514/1.J060131>
- [14] Talend. Available at <https://www.talend.com/resources/what-is-data-reliability/>
- [15] POKORNI S.: *Artificial Intelligence in Reliability and Maintainability*, 9th International Scientific Conference on Defensive Technologies OTEH 2020, Belgrade, 8-9 October 2020 (on line)
- [16] POKORNI S.: *Reliability and Availability of the Internet of Things*, Vojnotehnički glasnik / Military Technical Courier, 2019, pp. 588-600, 67(3), <https://doi.org/10.5937/vojtehg67-21363>