White Paper

Predictive and Prescriptive Maintenance in the Context of Automotive Functional Safety

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Terms and Definitions

Acronym	Definitions	Comment
ASIL	Automotive Safety Integrity Level	see ISO 26262:2018-1
DC	Diagnostic Coverage	see ISO 26262:2018-1
EFR	Early Failure Region	see section 2
FIT	Failure In Time	a unit that represents failure rates and how many failures occur every 10^9 hours
FR	Failure Rate	the frequency with which an engineered system or component fails expressed in failures per unit of time
HTOL	High-Temperature Operating Life	a reliability test
IFR	Intrinsic Failure Region	see section 2
LFM	Latent Fault Metric	see ISO 26262:2018-1
MTBF	Mean Time Before Failure	the average time between inherent failures of a mechanical or electronic system, during normal system operation
PMHF	Probability Metric for (random) Hardware Failures	see ISO 26262:2018-1
RUL	Remaining Useful Life	the length of time a machine is likely to operate before it requires repair or replacement
SPFM	Single-Point Fault Metric	see ISO 26262:2018-1
TTF	Time To Failure	amount of time an asset operates before it fails, equivalent to RUL
WFR	Wear-out Failure Region	see section 2

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1 Introduction

Reliability and safety are crucial features of automotive platforms, and semiconductor chips used in these architectures should comply with the applicable requirements mandated by ISO 26262 series of standards. The functional safety requirements are derived from the safety goals to reach "the absence of unreasonable risk due to hazards caused by malfunctioning behavior of electrical/electronic systems." In the standard, the malfunctions are classified as systematic failures[1] and random hardware failures. In this white paper, we consider the second type, which represents the failure appearing during the lifetime of the system due to random defects innate to the manufacturing or caused by operational conditions and usage. In addition, we describe the application of the time-to-failure (TTF) predictions in the context of estimation of the failure rate (FR), the subsequent improvement of the reliability of an electronic device, and the benefits of predictive and prescriptive maintenance methods.

The net benefits of TTF predictions, embodied as software applications for predictive and prescriptive maintenance, are presented in the context of electronic device reliability metrics: failure rate reduction, diagnostic coverage improvement, and longer operational lifetime. These three key performance indicators (KPIs), whose limits are defined in functional safety standards for mission-critical applications, are shown to be enhanced by the proposed methodology.

Upon TTF prediction of incoming permanent field defects, the predictive and prescriptive maintenance applications provide the actional insight to keep the fail-safe state of the system, which is fundamental for achieving the highest functional safety levels.

This white paper covers the following:

- **Base failure rate calculation with TTF**: For a given number of device samples, we consider not only the field failures in the cumulative failure fraction but also the predicted failures, to calculate the parameters of a Weibull instantaneous failure rate function, i.e., the failure rate of the intrinsic and wear-out regions of the reliability bathtub curve.
- **Reducing the failure rate by using predictive maintenance**: Assuming we use the TTF prediction for predictive maintenance, we can remove a device from the field before its failure occurs. The cumulative failures are reduced and the number of device samples as well, with the impact of reducing the overall failure rate.
- **Extending lifetime by prescriptive maintenance**: As the TTF prediction forecasts an expected failure within the useful lifetime of the device, the prescription of counteractions can postpone the loss of operations. The benefits of prescriptive

[1] These failures are deterministically induced by incorrect or flawed processes during development, manufacturing, or maintenance.

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maintenance are shown in terms of a reduction of the failure rate in the operational lifetime, or conversely postponing the beginning of the wear-out region.

2 FR Calculation Based on TTF Prediction

The reliability curve of an electronic device assumes the so-called bathtub shape with steep sides and a flat center. It includes three parts[2]: (1) early failure rate (EFR) region, the first part is a decreasing failure rate; (2) intrinsic failure rate (IFR) region, the second part is an almost constant and much lower failure rate; and (3) wear-out failure rate (WFR) region, the third part is an increasing failure rate.

The first region EFR is driven by gross defects, which are normally screened out by testing before shipment. Later in the field during the useful life we assume the failures are due to either (a) latent defects escaping the burn-in tests, (b) random defects or soft errors, such as transient faults caused by sub-atomic particle strike, and (c) material wear-out defects or failures caused by aging.

In this paper, we are not going to consider further the failures screened at production but focus on the field failures after it. Nonetheless, it is worth mentioning that a sensitive outlier detection mechanism is expected to reduce the number of unscreened latent defects which escape the production[3]. Furthermore, we are going to discuss the permanent errors and defects, not the transient ones.

By knowing the cumulative fraction of defective devices, it is possible to plot the number of failures vs. time in a Weibull chart and extract the characteristic Weibull parameters for shape (β) and scale (t_{63}). The Weibull failure rate or hazard function:

$$\lambda(t) = \frac{\beta}{t_{63}}\left(\frac{t}{t_{63}}\right)^{\beta-1}$$

In practice, we must consider the three regions as independent contributors and calculate the Weibull parameters using an individual liner fit in a log-log scale.

In Figure 1, there is an example of the Weibull chart for a hypothetical set of data described in Table 1.

[2] Reference chapter 7 of J. W. McPherson "Reliability Physics and Engineering", 2nd edition, Springer.

[3] See reliability tests described in "Quality and Reliability Manual" ISSI, chapter 3. For example, PAT Part Average Testing https://www.issi.com/WW/pdf/q_r_manual.pdf.

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TABLE 1
Observed failure data for 5000 devices in total.

Observed Failures										
Time (year)	1	2	3	4	5	6	7	8	9	10
N° of failures	1	2	2	2	2	2	2	5	15	25

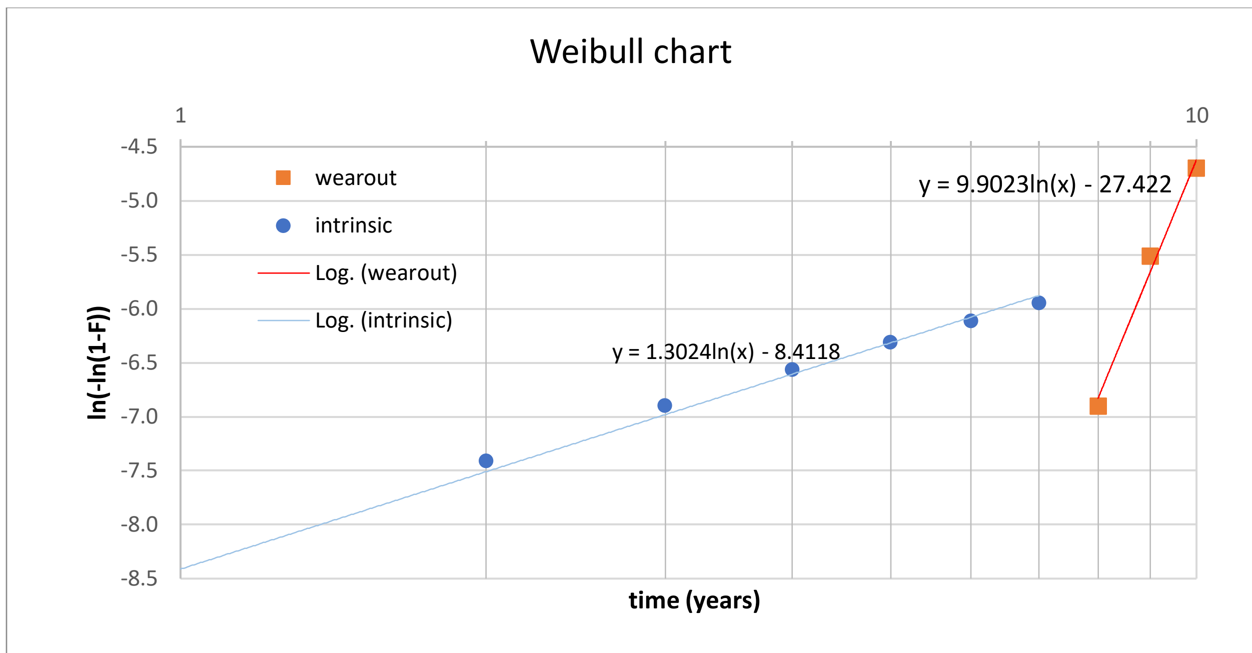

Figure 1: Weibull chart of the IFR and WFR regions.

We can extract from the chart the shape factor β as the slope of the logarithmic fit, and the scale factor t_{63} as the intercept with the y-axis.

Let us consider the following two methods to calculate the reliability of a device: (a) collecting the empirical field data from the operational life of the device, or (b) accelerating the time-to-failure process increasing the operating conditions.

Assuming we can predict by when a device under observation is going to fail by monitoring the performances (also known as TTF). At any moment of the device's lifetime, we can forecast the cumulative failure fraction distribution. In other words, the concept is to estimate the Weibull parameters by combining the observed and the predicted device failures.

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As an example, let us assume that we are observing the same 5000 devices as described in Table 2. However, instead of waiting 10 years to collect the field data, we can use the TTF prediction at an earlier moment, for example after four years. The failures after the fourth year are forecasted by knowing the remaining time before the failure of the device. In other words, TTF determines in which column of the table we count the predicted failure.

As in any field-data analysis, how to split the data between the intrinsic and wear-out regions is an arbitrary choice, based only on the observation of a rapid increment of the number of failures. In the table example, we arbitrarily decided that the wear-out region starts when the predicted failures are double the average of the precedent years.

TABLE 2
Observed and predicted failure data for 5000 devices in total.
After the fourth year, the data is predicted.

Observed and Predicted Failures										
Time (year)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
N° of observed failures	1	2	2	2						
N° of predicted intrinsic failures					2	2	2			
N° of predicted wear-out failures								4	16	23

We assume uniform data across time for the latent and random defects in the constant failure rate region, therefore the observed and predicted numbers shall be consistent and continuous, even if the observable degradation in performance could be very quick and without prior notice, therefore difficult to be predicted with accuracy.

On the contrary, the wear-out effects are much slower and easier to be observed with the proper coverage of data. In this case, the predictions are typically more accurate, and several techniques are available, including model-based, analytical-based, or knowledge-based[4] techniques.

If we consider a reliability test such as high-temperature operating life (HTOL), it will determine the expected failure rate during the operating conditions. The JEDEC 22-A108 standard defines the minimum amount of devices that must be considered and the acceptance criteria (max number of accepted failures)[5]. The survivor devices in a reliability test may be on the verge of failure, but it would not be visible in the traditional pass/fail metrics. Using parametric

[4] For a survey of the techniques, "Overview of Remaining Useful Life Prediction Technologies." C. Okoh et al. / Procedia CIRP 16 (2014) 158 – 163.

[5] See https://www.jedec.org/sites/default/files/docs/22A108D.pdf

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measurements of the performances and conditions of the device, it will be possible to estimate the incoming TTF and increase the confidence of the reliability assessment.

In this section, we have covered:

- The reliability curve and the best-known methods to estimate the characteristic parameters of this curve, i.e. failure rate calculation.
- Failure rate estimation of a device by considering the predicted failures TTF to anticipate the field data of an uncomplete data set, such as after a few years of a new device in the market and much before the device's end of life. The early availability of such data can play a key role in the quantitative functional safety analysis (e.g. FMEDA) of new systems, which use new technologies for the first time and are not extensively proven in the field yet.

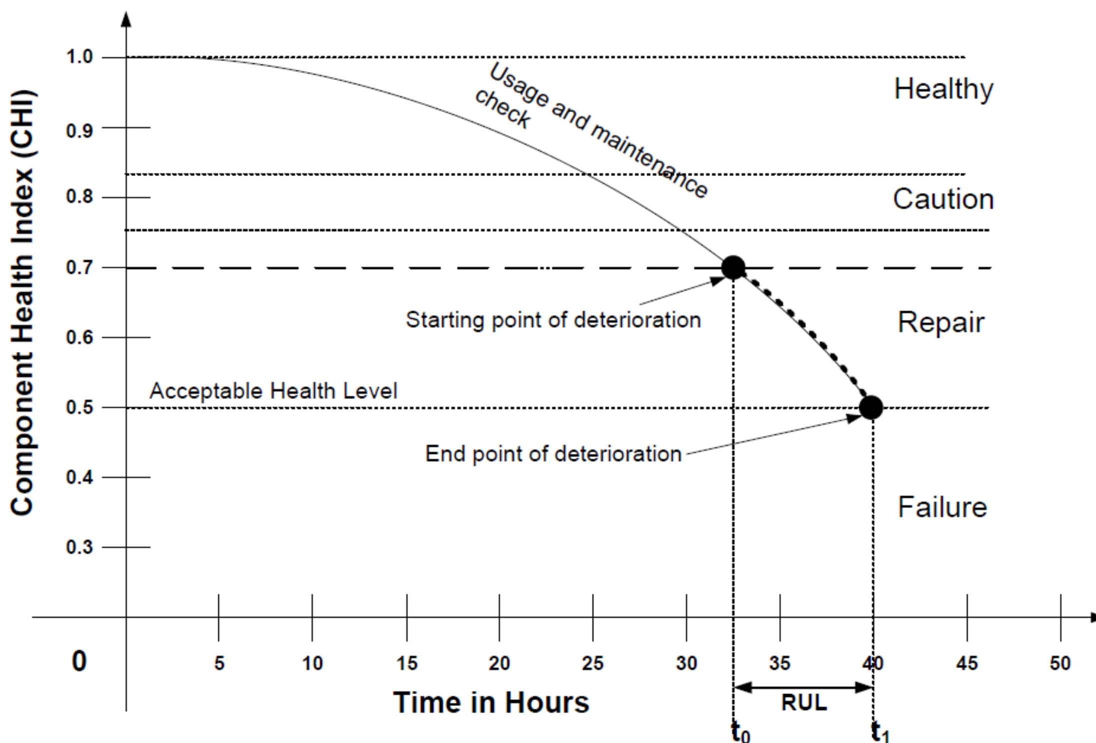

Figure 2: Chart of parametric data of device health vs. lifetime in hours (taken from "Overview of Remaining Useful Life Prediction Technologies." C. Okoh et al.). The degradation over time of the health index can be used to estimate the remaining useful life (shown as RUL in the picture) before a failure. RUL and TTF are equivalent in our case.

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3 FR Reduction by Predictive Maintenance

The ISO 26262 series of standards defines four different Automotive Safety Integrity Levels (ASIL), as shown in Table 3. Depending on the ASIL, the hardware architectural metrics should be calculated and fulfilled, including single-point fault metric (SPFM), latent fault metric (LFM), and probabilistic metric for hardware failure (PMHF), which defines the failure rate target of the system, or of the hardware element of the system.

TABLE 3
ISO 26262 Automotive Safety Integrity Levels (ASIL)

ASIL	SPFM	LFM	PMHF
A	Not relevant	Not relevant	< 1000 FIT
B	≥ 90%	≥ 60%	< 100 FIT
C	≥ 97%	≥ 80%	< 100 FIT
D	≥ 99%	≥ 90%	< 10 FIT

Under the term "predictive maintenance", we consider all the techniques which are designed to forecast the root cause of an incoming in-service device failure and when it will happen. The main promise of predictive maintenance is to allow convenient scheduling of maintenance services or preventive actions and to counteract potentially safety related device failures and operational downtime. In this regard, a predicted failure never develops into an actual failure, which can be considered in the field data of the reliability studies. We propose to remove such devices from the field data, reducing both the number of observed devices and actual failures.

In Table 4, we present a numerical example. We assume that the predictive maintenance is capable to detect k=50% of the imminent faults, which can be both intrinsic/latent or wear-out failures. We also assume that there is a false-positive rate of h=10%, which can also spoil the quality of the results. Namely, if F is the real number of devices that are going to fail in the future of a sample size of N devices, the total number of predictions P is equal to:

$$\text{Predicted failures, } P = (k*F + h*(N-F))$$

Table 4 shows the hypothetical results of an application characterized by 50% detection and h=10%. At every yearly prediction, the predicted devices were removed from the field whether the prediction is correct or not, reducing the number of observed failures.

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TABLE 4
Observed failures with and without predictive maintenance.

Observed Failures and Predictive Maintenance										
Time (year)	1	2	3	4	5	6	7	8	9	10
N° of observed failures without predictive maintenance	1	2	2	2	2	2	2	5	15	25
N° of observed failures with predictive maintenance	1	0	2	1	1	2	1	2	8	13

In the example proposed, we observe that the shape parameters are not dramatically changed as we expected, but the scale parameter of the IFR region of the case with predictive maintenance is twice bigger in comparison to the case without prediction.

As a result, if we set the reliability requirement with a limit of 100 FIT, our example shows that the useful lifetime of the device is extended from almost 7 years to 8 years. Alternatively, the residual failure rate in the useful lifetime area is significantly improved by 20-50% FIT, which is a remarkable reliability improvement. See Table 5 for the Weibull parameters and Figure *3* for the reliability curves.

Table 5
Weibull parameters with and without predictive maintenance.

Parameters		Without predictive maintenance	With predictive maintenance
Intrinsic FR region	b	1,302	1,196
	t_{63} (years)	638	1585
Wear-out FR region	b	9,902	11,008
	t_{63} (years)	15,9	16,1

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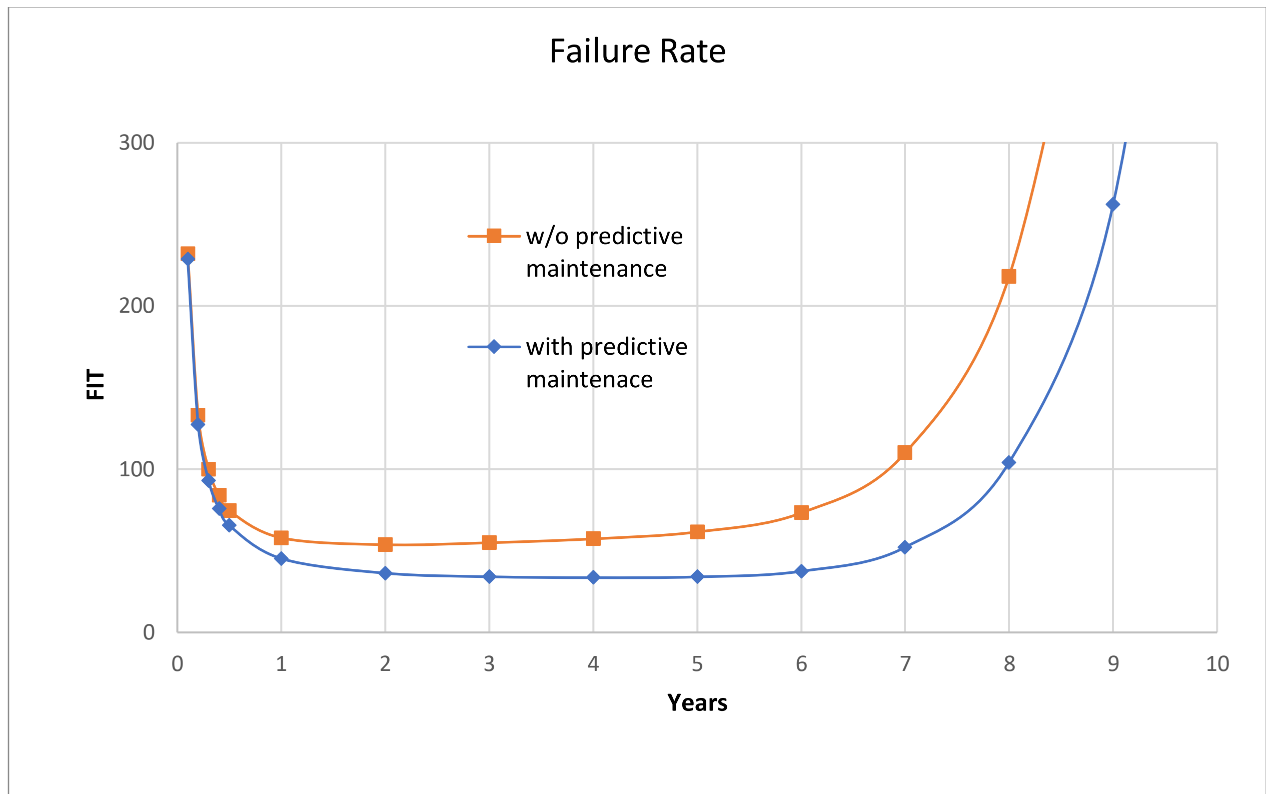

Figure 3: Reliability chart shows the combination of the three contributors, early, intrinsic, and wear-out regions for both cases, with and without predictive maintenance.

In this section, we have covered:

- The ability to reduce the in-service failures from the field data plays the same benefit as a preventive action, positively improving the robustness, reliability, and intrinsic failure rate.

4 Failure Rate and Prescriptive Maintenance

Prescriptive maintenance is a concept that collects and analyzes data to produce specific recommendations to reduce operational risks.

At the core of both predictive and prescriptive maintenance, there is the use of sensors to collect data about the conditions and performances of a device, to monitor their behavior and evolution in time, and the ability to forecast their degradation to anticipate the occurrence of a fault.

If predictive maintenance aims to prevent unexpected failures by repairing or removing the device promptly, the prescriptive concept recommends actions to change the future outcome by adapting the operational conditions of the device.

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Some of the random hardware faults occurring in the intrinsic failure region are difficult to be predicted, if at all[6]. Therefore, it is even more difficult to avoid their outcome by changing the operational conditions. On the other hand, the aging of the device is typically a time-dependent effect and can be modeled as a continuous degradation of observable KPIs. By parametric measurements of characteristic health or performance indicators, it is possible to observe the impact of wear-out and predict their trend over time.

The operational state of a device determines the device stress, therefore the aging speed.
Let us consider what we can do to reduce the operational workload of a device in a given moment of its life, thus reducing the overall stress.

It may not be possible to influence the external contributors, such as the ambient temperature, which may be fully independent and outside of our control. However, we may influence the other operational conditions impacting the operational state of the device, such as voltage and frequency, and the software application in execution.

For example, we can change the software application utilization of hardware by restricting the number of software processes in execution or disabling non-essential jobs, or, for a computer architecture cable of dynamic voltage scaling, we can constrain the overvolting or minimum frequency. There are two main consequences—risk of failure reduction and performance drop.

Such a strategy is similar to the so-called “limp-home mode” used in any modern electronic controlled combustion vehicle, when, in case of failures, the throttle is set to fast enough to get the transmission but not so fast that driving may be dangerous. The system’s safe state is maintained at the cost of a partial reduction of the system availability.

In Figure 4, we are considering the same example as discussed in the previous section on FR Reduction by Predictive Maintenance In this case, the wear-out faults are delayed because we assume a reduction of the operational stress as soon the degradation is below a critical threshold to choose arbitrarily. If the reliability requirement is defined as FR<100 FIT, the resulting useful lifetime is extended from 8 to 9 years.

[6] i.e. soft error caused by secondary particles from cosmic rays.

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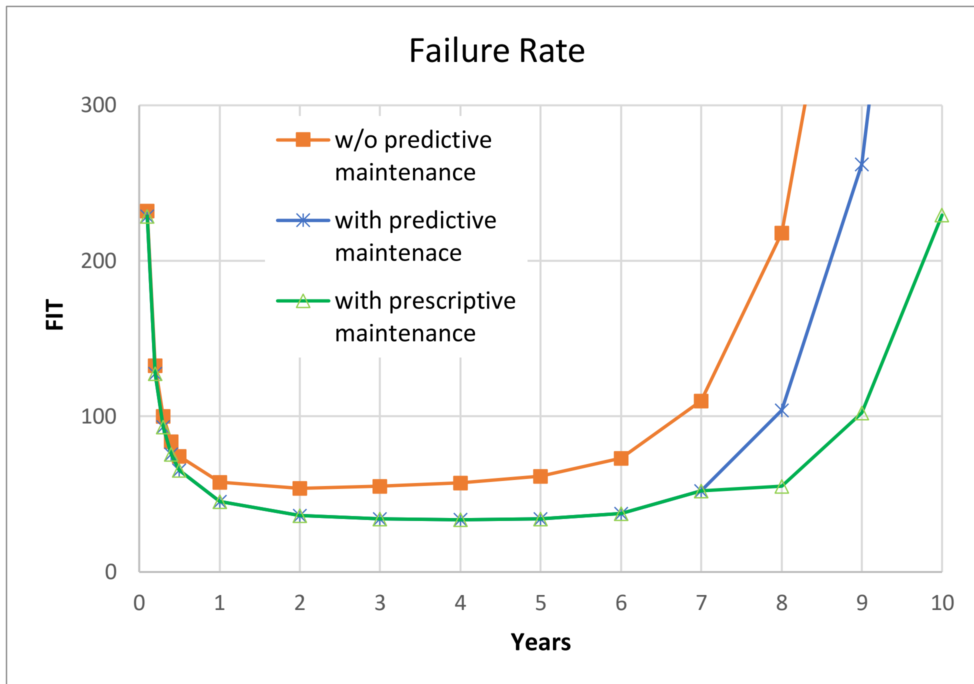

Figure 4: The operational lifetime is defined by three main contributors: (1) The latent defects left unscreened after manufacturing, such as burn-in tests. (2) Random external events that can critically impact the device and cause an internal failure, such as alpha particle changing memory bits or electromagnetic interference (EMI) influences. (3) Early degradation of devices, which depends on how far is the average lifetime from the end of the operational lifetime and how wide is the standard deviation of the probability distribution. The duration of the operational lifetime in green depends on how long the failure rate of the system remains below the safety target, for example, FR<100 FIT. We can notice how there is a notable extension of the useful lifetime with predictive and prescriptive maintenance as the FR remains lower 100 FIT for a much longer period.

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5 Conclusions and Outlook

Predictive and prescriptive maintenance are extremely promising approaches for preventing system breakdowns and unnecessary maintenance, nevertheless not exclusively in these regards. In this white paper, we presented the benefits of such techniques in the context of functional safety, under the premise that the ability to forecast hardware failure is not only a reliability or quality KPI, but it plays a crucial role in keeping the system in its safe state.

In the latest edition of ISO 26262:2018-1, a safety mechanism is defined as a "technical solution implemented by E/E functions or elements, or by other technologies, to detect and mitigate or tolerate faults, or control or avoid failures, in order to maintain intended functionality, or achieve or maintain a safe state." In our opinion, the keywords here are failure avoidance and maintaining a safe state. Yet, in the current edition of the standard for Functional Safety for Road Vehicles, the intention of the authors seems to focus on reactive safety by detection of a fault, rather than proactive safety by anticipating its occurrence.

Let us consider the case of a hardware device, that according to the required metrics of the standard, is classified as ASIL-B out-of-context. As described in Table 3, the failure rate is under 100 FIT (PMHF), and it has a 90% coverage by the safety mechanisms to prevent risk from single-point faults in the hardware architecture (SPFM). What if, by the combination of predictive and prescriptive mechanisms, we would be able to reduce the actual failure rate below 10 FIT? By the current definitions, we would not be able to classify the system element at a higher ASIL, because the *prognostic coverage* (also known as the proportion of the hardware element failure rate that is forecasted and anticipated by the implemented predictive or prescriptive maintenance[7]) does not contribute to the SPFM or PMHF metric.

The increased use of predictive and prescriptive maintenance methods could lead the industrial community to consider one of the following two proposals, or similar:

1. Define separate hardware architectural metrics dedicated to predictive and prescriptive maintenance coverage and account for them in the final PMHF calculation. For example, this could be considered in the development of the next version of ISO 26262.
2. Consider predictive and prescriptive maintenance in the calculation of the intrinsic failure rate ahead of SPFM, LFM and PMHF calculations. This proposal could be adopted today and could benefit those projects where, given higher complexity and area, minimum targets of SPFM and LFM still does not allow to meet the PMHF requirement for the system.

[7] A careful reader would notice that the definition of the *prognostic coverage* is modeled upon the diagnostic coverage definition 3.33 of the ISO 26262-1 standard.

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Visibility from within electronics is an important trend in automotive, as in other domains, where IoT, connectivity, and the high number of sensors and data are becoming available and convenient. Continuous, in-mission mode health and performance degradation monitoring are the key elements for offering proactive safety.

As in the past, it is expected to be a virtuous circle. As the technology is available, the limits are updated to push the industry into the adoption of the most advanced technologies and to sharpen the reliability requirements of standards and legislation.

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