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# A Direct Method for Determining Design and Support Parameters to Meet an Availability Requirement – Parameters Affecting Both Downtime and Uptime

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**Abstract:** This paper uses a discrete event simulation based direct method that allows an availability requirement to be used to predict required logistics, design and operation parameters. Parameters that affect both downtime and uptime are addressed in this paper.

***Keywords:*** *Availability, prognostics and health management (PHM).*

## 1. Introduction

A direct method based on discrete event simulation that uses an availability requirement to determine unknown system design and support parameters has been developed [1]; the approach is general and can be used when uncertainties are included and the availability requirement is represented as a probability distribution. Figure 1 in [1] summarizes the general steps to formulate and execute this methodology.

Two distinct types of system parameters exist: Type I affecting either uptime or downtime (but not both), and Type II concurrently affecting both uptime and downtime. Type II parameters are addressed in this paper (Type I parameters were addressed in [1]).

## 2. Determining Type II Parameters

For Type II parameters, a change in the value of the parameter produces a change in both uptime and downtime, there are three unknown quantities: 1) the unknown parameter, 2) the downtime and 3) the uptime; and three relationships need to be established to solve for the unknown quantities. The uptime can be expressed as a function of the unknown parameter; to generate the first relationship. Secondly, the unknown parameter explicitly affects the downtime, so downtime can be expressed as a function of the unknown parameter. Availability is by definition a function of uptime and downtime; hence the third relationship. A closed-form analytical solution cannot be determined when solving for the unknown parameter from known quantities (e.g., probability distributions) since the sequences of the accumulated event outcomes are only generated as the simulation progresses through time.

Here we apply the methodology to determine the minimum allowable reliability, i.e., the time-to-failure (*TTF*) of the line replaceable units (LRUs) that is necessary to meet the availability requirement. We assume that, the reliability of each LRU is represented by its *TTF*, where each *TTF* corresponds to the period of time until the occurrence of the next actual failure. To see that *TTF* is a Type II parameter consider the following scenario: replenishment LRUs will be delivered one year from now and the inventory is currently out of LRUs. The system (the socket), that is drawing LRUs from the inventory, will be in the up-state as long as the current LRU doesn't require replacement, thus the system

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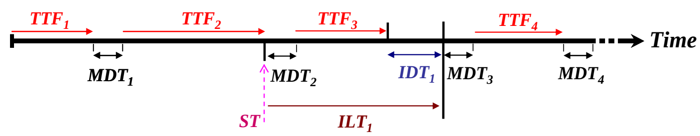



**Figure 1:** TTF Implication on the Operational Timeline

uptime depends on the *TTF* of the current LRU. Also, the system downtime could be minimized if the LRU currently in the socket does not require replacement until the replenishment spares are delivered (e.g., one year from now). However, as soon as the LRU requires replacement, the system will be down until additional spare LRUs are received. Thus, system downtime is also dependent on the *TTF* of this LRU.

To demonstrate the derivation of the *TTF* for a specific availability requirement, the methodology has been implemented within the discrete event simulation. The model samples the required availability distribution and other quantities, and uses the quantities to solve for a value of the unknown parameter. This process is repeated for each socket in the population. The resulting parameter distribution is the required quantity to meet the availability requirement. The case study inputs are: 3 initial spares for each socket, the threshold for spare replenishment is ≤ 1 in the inventory per socket, 2 spares per socket are purchased at replenishment, and the spare replenishment lead time (*ILT*) is 18 months.

The sampled *TTF* values are used to predict maintenance events. In the unscheduled maintenance case, the sampling of the *TTF* values predicts the date of the next maintenance event associated with a failure of a system. Spares are drawn from the inventory as needed to support maintenance. Once the inventory reaches its threshold value, additional spares are ordered, and the replenishment spares are delivered after the *ILT*. Figure 1 illustrates this scenario, where *MDT* is maintenance downtime, *ST* is the spares threshold (once the inventory level drops below this value, additional spares are ordered), and *IDT* is inventory downtime (the system is down waiting for spares).

Notice that the accumulated uptime (*UT*) accounts for all system's uptimes. This includes the system's uptime while using the inventory initial spares (*IS*) and the system's uptime while using inventory replenishment spares (*RS*). The *RS* could be ordered multiple times as needed,

$$\sum UT = (IS)(TTF) + \sum (RS)(TTF) \quad (1)$$

The accumulated downtime (*DT*) includes the maintenance downtime (*MDT*) and the inventory downtime (*IDT*),

$$\sum DT = \sum IDT + \sum MDT = \sum (ILT - (ST)(TTF)) + \sum MDT \quad (2)$$

The summations in (1) and (2) do not refer to the analytical summations, but to the accumulation of sequential events, which are determined as the simulation progresses through time. Also, the model is probabilistic, this means each sample of the same quantity, i.e., system parameter, could result in a different event outcome.

The operational availability is the accumulated uptime over the total operational time (i.e., sum of the total accumulated uptime and downtime),

$$A_O = \frac{\sum UT}{\sum UT + \sum DT} \quad (3)$$

For example, the $k^{th}$ *TTF* value could be derived by combining (1), (2) and (3). The $k^{th}$ *TTF* corresponds to the $k^{th}$ downtime, where the $k^{th}$ downtime could be a maintenance downtime, inventory downtime, or any other logistics downtime. The summations in (4)

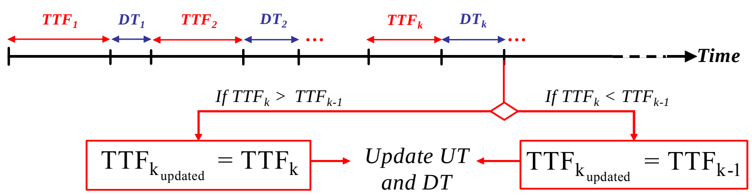



**Figure 2:** Updating the TTFs, UTs and DTs

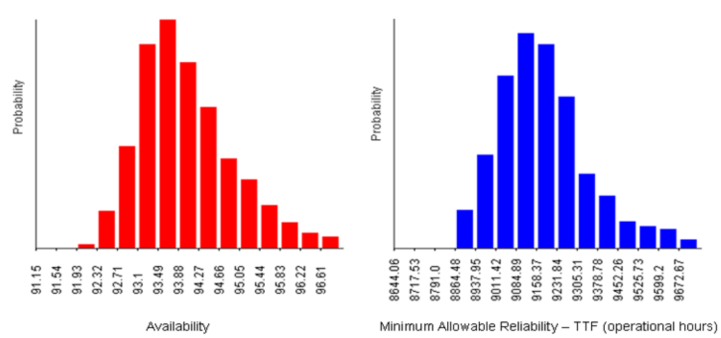
do not refer to analytical summations, but to the accumulation of events outcomes and sequences. Therefore, the right side of (4) does not explicitly include the "*k*" subscript,

$$TTF_k = \frac{\sum ILT + \sum MDT}{\frac{1-A_O}{A_O}\left(IS + \sum RS\right) + \sum ST} \tag{4}$$

The modeling of the operational timeline illustrated in this section is not unique i.e., (1), (2) and (4) could vary. Although, different models could provide different equations, the steps of the procedure remain the same.

After every downtime, the *TTF* is computed. Figure 2 illustrates the process of updating the computed *TTFs*. After every downtime, the computed *TTF* is compared to the previous value; if the current value is greater than the previous one then the current value is used. But if the current value is less than the previous one, then the current one is substituted for the previous value. Once, the current *TTF* value is updated, this new *TTF* requirement is imposed on the uptime and downtime values through (1) and (2). Finally, the model uses the updated *TTFs*, *UTs*, and *DTs* to compute other quantities of interest.

The availability requirement considered in this example case is shown in Figure 3a. Figure 3b shows the resulting TTF distribution (for unscheduled maintenance). The required availability distribution and other quantities (inputs) that may be described as probability distributions are sampled and used to solve for a single value of *TTF*. This value represents the minimum *TTF* value (minimum allowable reliability) that is necessary to meet the sampled required availability in the environment defined by the sampled values of all the other input quantities. This process is repeated for each socket in the population, resulting in a histogram of minimum allowable *TTFs*. Note a verification




(a) (b)

**Figure 3:** (a) Required Availability Distribution; (b) Computed Minimum Allowable Reliability (*TTF*) in Operational Hours, for an Unscheduled Maintenance Policy

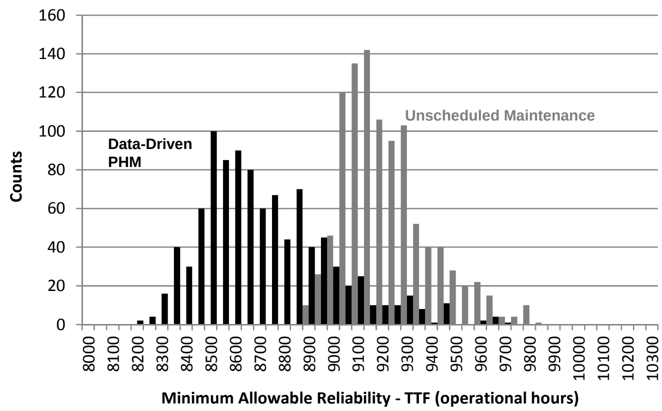



**Figure 4:** Computed Minimum Allowable Reliability (*TTF)* Distribution for Unscheduled Maintenance and Data-Driven PHM to Meet an Availability Requirement. Both Maintenance Approaches Satisfy the Same Availability Requirement.

of this process was performed in [2]. Using the same inputs defined in [1] for data-driven PHM, a determination of the *TTF* to fulfill the same availability requirement in Figure 3a for an unscheduled maintenance approach and a data-driven prognostics and health management (PHM) approach applied to the same system has been performed – Figure 4.

Figure 4 shows the resulting *TTF* distributions using unscheduled maintenance and data-driven PHM, in light grey and black respectively. By comparing the resulting *TTF* distributions for unscheduled maintenance and data-driven PHM approaches, data-driven PHM has allowed a smaller *TTF* requirement. Thus using a data-driven PHM approach relaxes (relative to unscheduled maintenance) the required *TTF* to meet the imposed availability requirement. This is a powerful result since the methodology not only derives the necessary system parameters for a specific availability requirement, but it also reflects the impact of a PHM approach on the selected system parameters.

## 3 Discussion

It is important to note that the process described is not iterative. While the methodology includes operations that are repeated for every time step, every update of the unknown parameter happens at a different (later) time. Conventional iteration would imply that operations are repeated at each event to improve the result, or that the whole process (through all events) was repeated to improve the result – neither of these are the case. Because the process is not iterative, it is computationally simple and straightforward, the solution always exists and converges, and a real-time assessment could be performed.

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## References

[1] Jazouli, T., P. Sandborn, and A. Kashani-Pour, *A Direct Method for Determining Design and Support Parameters to Meet an Availability Requirement*, International Journal of Performability Engineering, March 2004, 10(2): 211-225.

[2] Jazouli T., and P. Sandborn. *Using PHM to Meet Availability-Based Contracting Requirements*, Proc. IEEE Int. Conf. on Prognostics and Health Management, June 2011.