

# Modeling Data Durability and Availability

Serkay Ölmez serkay.olmez@seagate.com

January 7, 2021

Acknowledgements: Ian Davies, Mike Barrell, John Bent, and Iman Anvari





## **Outline**

- Modeling Failures
  - Weibull Distribution
- Erasure Coding(EC)
  - General formalism, RAID 5& 6
- Hard Errors ( UREs )
  - Modeling durability with UREs
- Distributed Parity
  - Improving data durability with ADAPT
- Multi-Layer EC
  - Improving durability with two layers of EC
- Availability
  - Modeling data availability
- Appendix
  - MACH2 and ReMan



# **Goals & Summary**

### Goals

- · Provide a quick review of available models to compute data durability,
- Present an accurate and rigorous model,
- Establish a common language to compute these metrics.

### **Summary**

A quick survey on literature

- The durability and availability of data can be predicted accurately with Markov Chains:
  - Based on rigorous math, and verified with Monte Carlo simulations.
  - Supports Distributed Parity, ReMan, UREs, Weibull failure modes, and multi-layer EC.
  - Developed in collaboration with the CORTX architects & sales team.
- Advanced features, such as Online ReMan, can be modeled too:
  - We continue to work on modeling latest and greatest CORTX features.



# Modeling component failures

We will assume that individual component failures can be described by a Weibull distribution [10]. The failure probability density, cumulative failure distributions and the hazard rate (failure rate) are defined as follows:

$$f_{\alpha,\beta}(t) = \frac{\beta}{\alpha} \left(\frac{t}{\alpha}\right)^{\beta-1} e^{-\left(\frac{t}{\alpha}\right)^{\beta}},\tag{1}$$

$$F_{lpha,eta}(t) = \int_0^t d au f_{lpha,eta}( au) = 1 - e^{-\left(rac{t}{lpha}
ight)^eta},$$
 (2)

$$h_{\alpha,\beta}(t) = rac{f_{\alpha,\beta}(t)}{1 - F_{\alpha,\beta}(t)} = rac{eta}{lpha} \left(rac{t}{lpha}
ight)^{eta-1}.$$
 (3)

The actual values of  $\alpha$  and  $\beta$  vary from product to product:  $\beta$  is expected to be between 1 and 2.

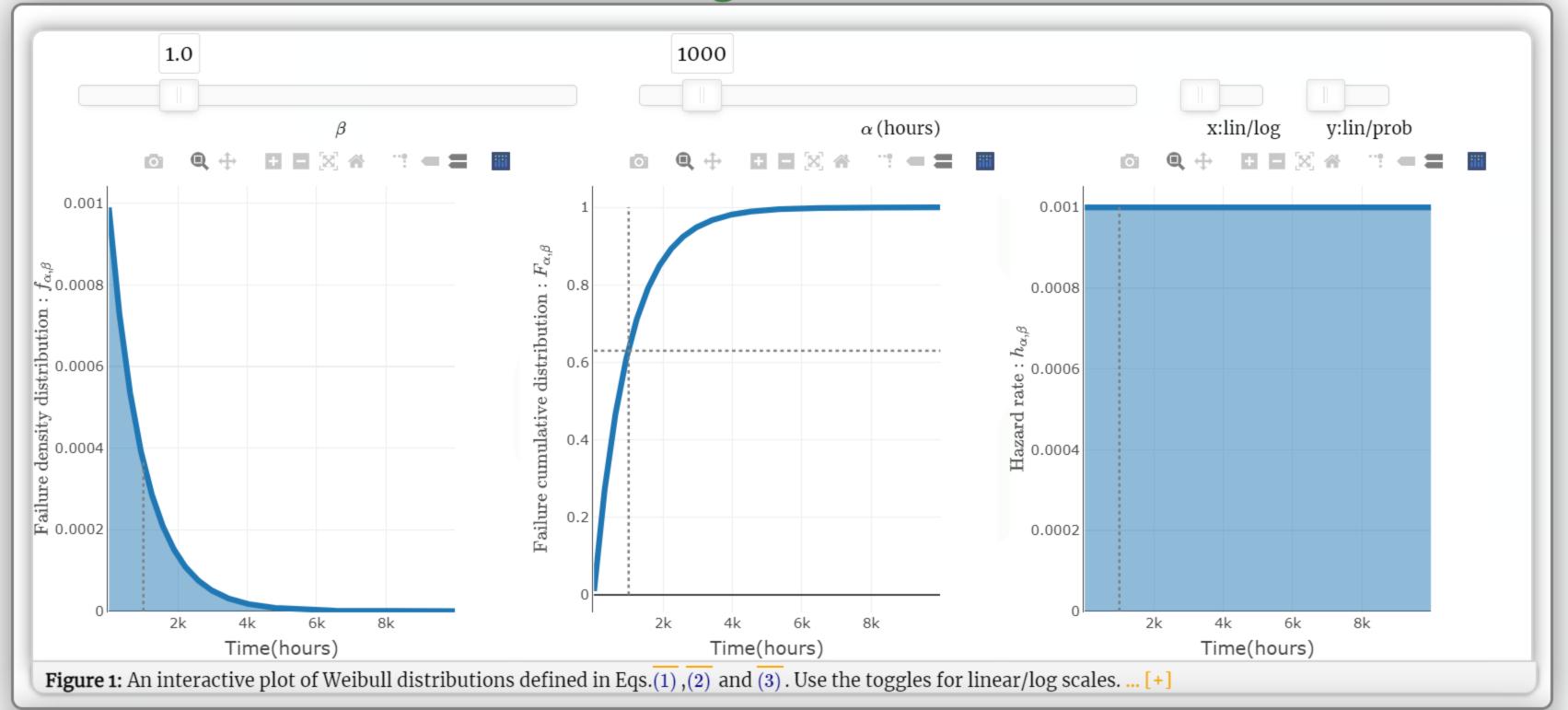
 $\beta = 1$  gives the exponential distribution, which has completely random head failure times with a fixed failure(hazard) rate:  $h_{\alpha,\beta}(t) = \frac{1}{\alpha} \equiv \lambda$ . This simplifies Eqs. (1),(2) and (3) to:

$$f_{\lambda}(t) = \lambda e^{-\lambda t}, \quad F_{\lambda}(t) = 1 - e^{-\lambda t}, \text{ and } \quad h_{\lambda}(t) = \lambda.$$
 (4)





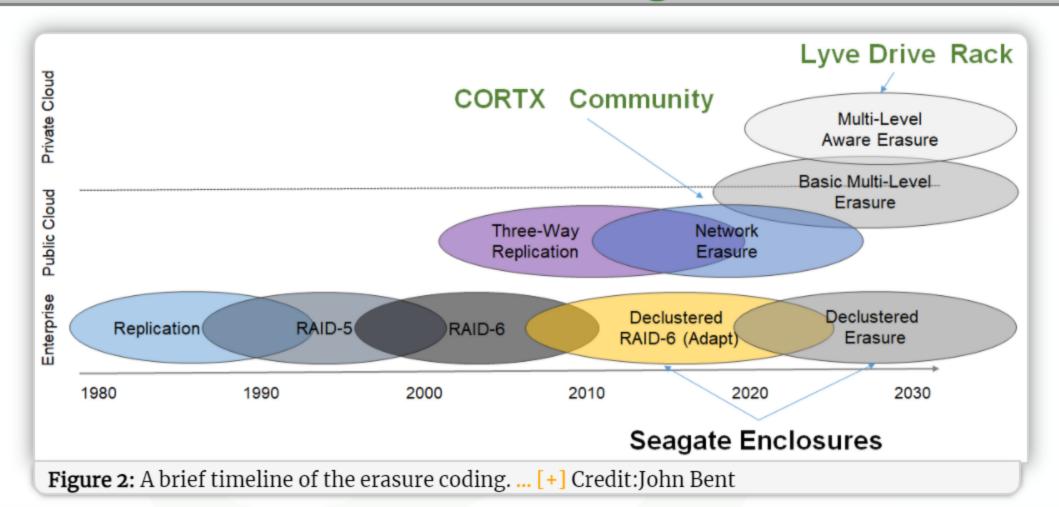
# Visualizing failure distributions



- It is important to understand how the storage devices fail. Weibull is typically a good fit.
- No matter how reliable individual devices are, failures are inevitable.



# **Erasure Coding**



- The simplest way of creating redundancy is replication, but this has a very poor capacity efficiency.
- RAID 5 and Raid 6 introduce parities to protect data against device failures.
- Seagate enclosures supports declustered RAID6, which can be coupled with a top layer EC in CORTX to get the highest durability with best capacity efficiency.



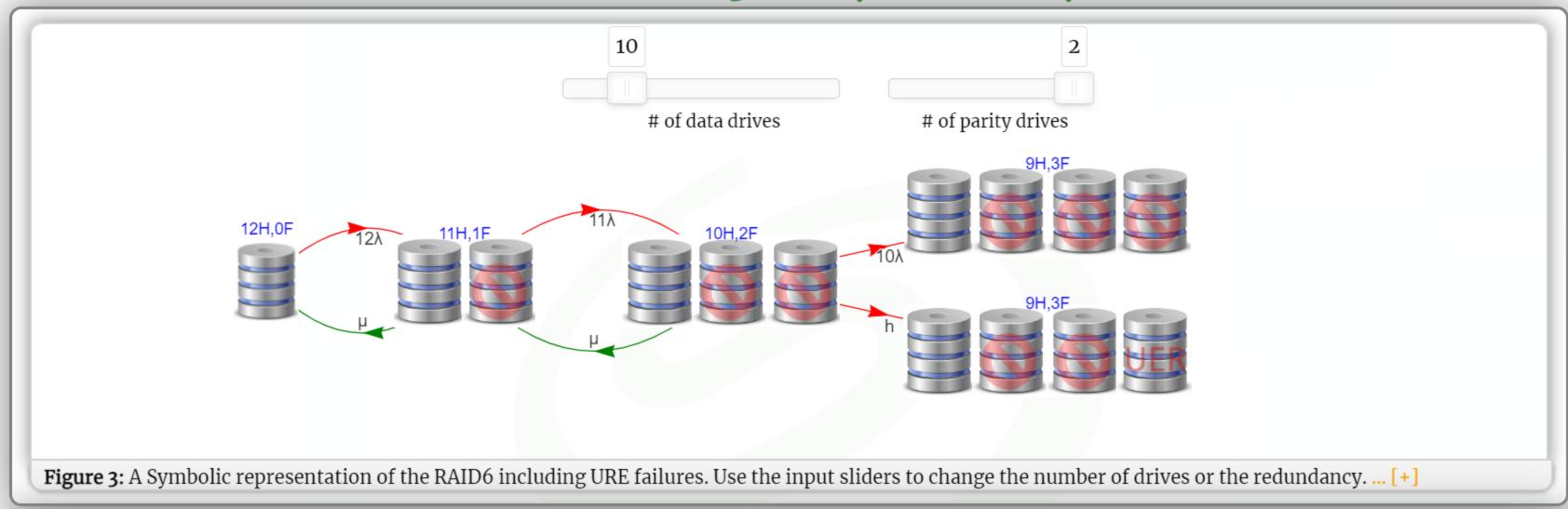
# **Creating Redundancy**

- EC adds fault-tolerance by creating redundant data pieces.
- Data is distributed across different storage media.
- Simplest example: compute and store the parity data.
  - Given two bytes of data:  $B_1 = 01001001$  and  $B_2 = 11011010$
  - The parity data:  $P = B_1 \oplus B_2 = 10010011$
- Assume the drive that stored  $B_1$  fails:
  - Compute  $P \oplus B_2$ , which is equal to  $B_1$ .
- The data on the failed drive can be reconstructed.
  - Fault tolerant to one drive failure.
- *c* pieces of redundancy data:
  - Parities computed using Reed-Solomon algorithm.
  - Fault tolerant to c simultaneous drive failures.
- Main Question: What is the probability of having c+1 simultaneous failures?





## RAID 5 & 6 (with URE)



- The red arrows represent drive failures. Rate is scaled with the total number of drives:
  - $\lambda$  is the failure rate per drive, and  $n\lambda$  is the total failure rate for n drives.
  - The arrow denoted with h represents the data loss due to UREs to be discussed in more detail later.
- The green arrows represent repairs. Failed drives are replaced, and data is rebuilt.
  - The repair time,  $1/\mu$ , depends on capacity and DR. It may be as long as several days.
- Data is lost when the system moves to the right-most state.
  - **Key metric: Mean Time to Data Loss (MTTDL)**: it is a function of n, c,  $\lambda$ ,  $\mu$ , drive capacity and UER.





# Durability with minimal math

Here we review a few different approaches in the industry to compute data durability.

Press down arrow to navigate this sections.





## The simplest model

### Consider the following set up:

- (n) drives [20], capacity(C): [16] TB, redundancy(c): [3], recovery speed (S): [50] MB/s, and AFR: [1] %
  - At this recovery rate, the recovery time from a drive failure is: (16 TB)/(50MB/s) = 3.7 days.
  - The probability of losing a single drive in 3.7 days is: 1 % \* (3.7 days/365)= 0.01%
  - The system will lose data when there are 4 failures in 3.7 days, which has the probability: (0.01%)4.
  - Data durability = 1 Probability of 4 failure(s) in 3.7 days = 1  $(0.01\%)^4$  = 15 nines.

Number of nines is defined as the instances of leading 9's in reliability: 0.998 has 2 nines, 0.9991 has 3 nines.

number of nines = Floor 
$$(-log10(1 - Durability))$$
 (5)

- This model is very simple, but... it is wrong!
- The metric calculated is **not** the data durability for an 3-redundant EC, it is for 1+3 [original+3 mirror(s)].
  - Note that the total number of drives, 20, did not even enter the equations!
  - There are binomial(20,4)=4845 combinations to choose 4 failure(s) out of 20 drives.
- This is not even the durability for over a year, it is just over 3.7 days. There are 99 such frames in a year.
- With the binomial coefficients and the # frames/year included, this model over-reports durability by at least 5 nines.
- This model also ignores UREs.



### The BackBlaze Model

This is a model introduced by  $\oint BACKBLAZE [11], [12].$ 

- (n) drives 20, capacity(C): 16 TB, redundancy(c): 3, recovery speed (S): 28.5 MB/s, and AFR: 0.4 %.
  - The recovery time from a drive failure is:  $T \equiv \frac{C}{S} = 6.5$  days.
  - The AFR value can be converted to the failure rate as:  $\lambda = -\frac{\ln(1-AFR)}{\text{year}} \simeq \frac{AFR}{\text{year}} = 0.004/\text{year}$ .
  - The probability of a given drive to fail in 6.5 days is:  $p_f \equiv \lambda T$  = 0.01%.
  - The system will **not** lose data when there are at most 3 failures in 6.5 days.
    - The probability of not losing data in 6.5 days is:  $p_{\text{no-loss}} = \sum_{i=0}^{c} \binom{n}{i} (p_f)^i (1-p_f)^{n-i}$  =13 nines.
  - There are  $N_F = \frac{365}{T} = 56$  such frames in a year.
    - The probability of not losing data in a year is:  $(p_{\text{no-loss}})^{N_{\text{F}}}$  =11 nines.

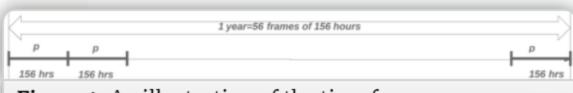
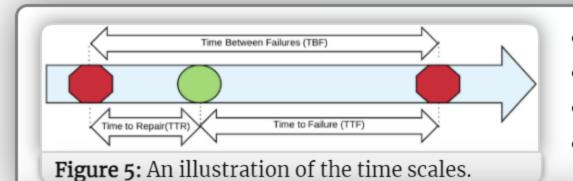


Figure 4: An illustration of the time frames.

- This model is still simple, but... it has a few issues:
  - The segmentation of a year into 56 chunks of 6.5 days implies that data is lost only when 4 failures happen in a given frame. The cases of 4 failures within in 6.5 days but spanning two subsequent frames are missed.
  - It is implicitly assumed that every frame starts with a 3-redundant system. In reality, there may be up to 3 ongoing repairs exiting the previous frame, and a single drive failure early in the next frame will cause data loss.
- Ignoring UREs, BackBlaze model works reasonably well in the low AFR limit (up to a factor of  $\sim$  2).
- Including UREs will reduce the data durability by ~2 nines.



### The most intuitive model



- Figure plotref\_avaldef\_NTT shows the time scales in a repairable system.
- A system of n drives has the Mean Time To Failure: MTTF =  $1/(n\lambda)$ .
- A failed drive is replaced, and rebuilt. Mean Time To Repair:  $\mathrm{MTTR} = 1/\mu$ .
- Fraction of the time spent for repair:  $\frac{MTTR}{MTTF+MTTR}$
- Fraction of the time spent for repair:  $\frac{\text{MTTR}}{\text{MTTF+MTTR}} \simeq \frac{\text{MTTR}}{\text{MTTF}} = \frac{n\lambda}{\mu}$  (MTTF  $\gg$  MTTR).
- There are N-1 drives left running. The rate of failure:  $(n-1)\lambda$
- Multiply this rate with the fraction of time in recovery:  $\frac{n\lambda}{\mu}(n-1)\lambda = \frac{n(n-1)\lambda^2}{\mu}$ 
  - This is the rate of data loss. Inverting the expression:  $\text{MTTDL}_1 = \frac{\mu}{n(n-1)\lambda^2}$
- When there are two parity drives, we can iterate to get:  $\text{MTTDL}_2 = \frac{\mu^2}{n(n-1)(n-2)\lambda^3}$
- For c parity drives, we can recursively iterate to get:  $\text{MTTDL}_c = \left[\frac{\mu}{\lambda}\right]^c \frac{(n-c-1)!}{\lambda n!}$
- c=1 is a RAID5, and c=2 is a RAID6 setup.  $c\geq 3$  cases are referred to as Erasure Coding in general.
- This model is very intuitive, and works great, but... it is not clear how to include UREs.

# Durability with rigorous math

- Figure shows the Markov chain for a system of n drives with one redundancy.
- Markov chain represents state transitions and state probabilities  $p_j(t)$ .
- The change in  $p_j(t)$  is dictated by incoming and outgoing arrows.

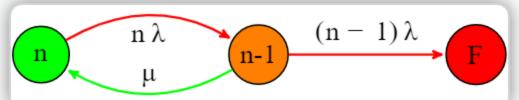


Figure 6: Markov Chain with one redundancy.

Show the details

- The state transitions are described by a set of coupled DEs.
- They can be solved by Laplace transforms.
- The equations are solved for the data loss state.
- The reliability:  $R(t) = 1 p_F(t) \sim e^{-t/\text{MTTDL}_1}$
- MTTDL<sub>1</sub> =  $\frac{1}{n(n-1)\lambda} \frac{\mu}{\lambda}$ .

$$\dot{p}_{n} + n\lambda p_{n} - \mu p_{n-1} = 0$$

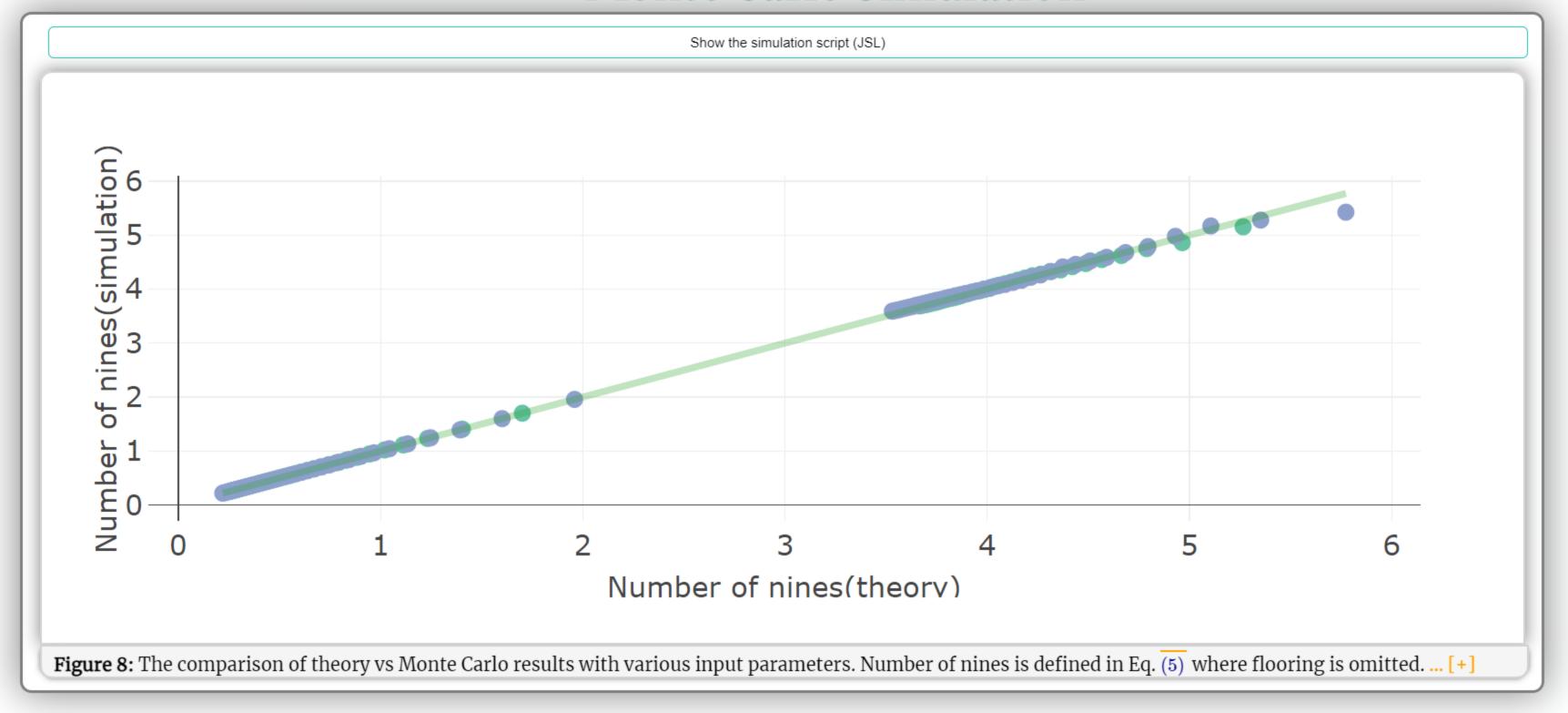
$$\dot{p}_{n-1} + (n-1)\lambda p_{n-1} + \mu p_{n-1} - n\lambda p_{n} = 0$$

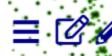
$$\dot{p}_{F} - (n-1)\lambda p_{n-1} = 0$$
(15)

- Markov chain analysis is needed to address complicated cases:
  - Declustered Parity (ADAPT),
  - Re-Manufacturing in the field (ReMan),
  - Generic Weibull distribution for drive failures ( $\beta \neq 1$ ),
  - Latent sector errors, i.e., hard errors (UREs).
- Most of the items above will be addressed in this presentation.

#### a

## **Monte Carlo Simulation**







# Silent data corruption (URE)

- UREs may arise due to thermal decays of bits. They are discovered only when data [is attempted to be] read.
- It is defined as the probability of a corrupted sector **per bits** read. A typical value is  $10^{-15}$ .
- With tens of TBs data, observing at least one corrupted sector is very likely [13].

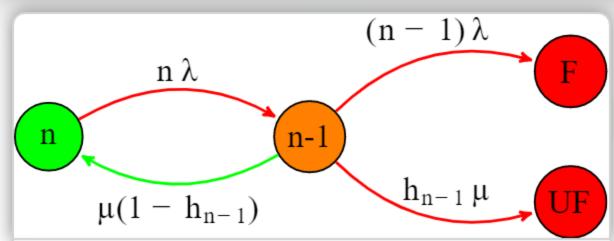


Figure 9: Markov chain with one redundancy with UREs.

• Figure on the left includes failures due to UREs.

$$S = egin{bmatrix} s+n\lambda & -\mu(1-h_{n-1}) & 0 \ -n\lambda & s+(n-1)\lambda+\mu & 0 \ 0 & -(n-1)\lambda-h_{n-1}\mu & s \end{bmatrix}$$

•  $h_{n-1}$  is the probability of observing UER(s) in critical repairs:

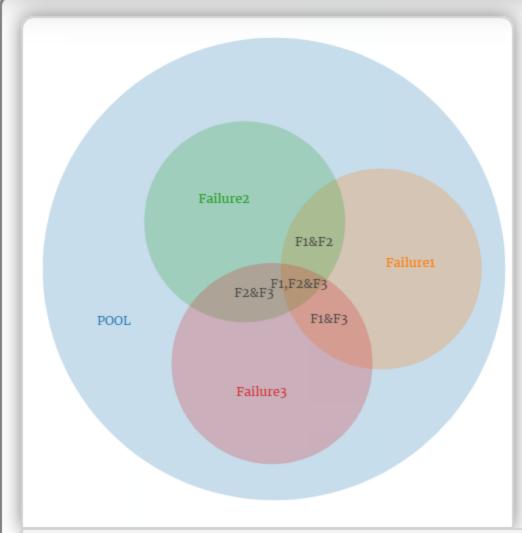
$$h_{n-1} \equiv 1 - (1 - \text{UER})^{N_{\text{bits}}} \simeq 1 - e^{-\text{UER} \times N_{\text{bits}}} = 1 - e^{-\text{UER} \times (n-1) \times C_{\text{bits}}}$$
 (16)

- Finding the poles of the determinant we get:  $\frac{1}{\text{MTTDL}} = \frac{\mu}{n\lambda[(n-1)\lambda]} + \frac{1}{1/(n\lambda)}h_{n-1}$ 
  - This is an harmonic sum of MTTDLs for Drive failure mode and UER failure mode.
  - The analysis can be extended to a generic c redundancy:  $\frac{1}{\text{MTTDL}_c} = \frac{1}{\text{MTTDL}_{c,\text{DF}}} + \frac{h_{n-1}}{\text{MTTDL}_{c-1,\text{DF}}}$
- For large data  $[UER \times (n-1) \times C_{\text{bits}} \gg 1]$ ,  $h_{n-1}$  is significant, and the second term dominates the durability.
  - Ex: UER =  $10^{-15}$ , n=20 and  $C=10\text{TB} \rightarrow h_{n-1}=1-(1-10^{-15})^{19*8*10^{13}} \simeq 1-e^{-1.52}=0.78$ .
- Sector level data durability of an EC with c parities is at the order of drive level durability with c-1 parities.

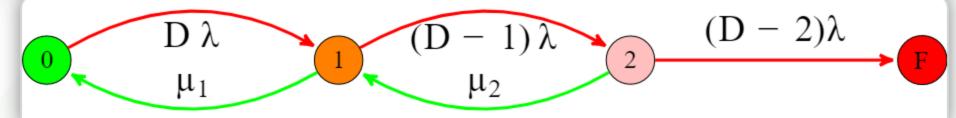


## Distributed Parity (ADAPT)

- Distributed raid (dRAID) uses all the drives in the pool to store data and parities.
- Rebuild is done by reading from all drives in the pool in parallel.
- ADAPT prioritizes the repair of critically damaged stripes[9]. This is the main reason for religain.



**Figure 10:** Venn Diagram of overlaps of 3 failures with 53-drive pool and EC size of 10.

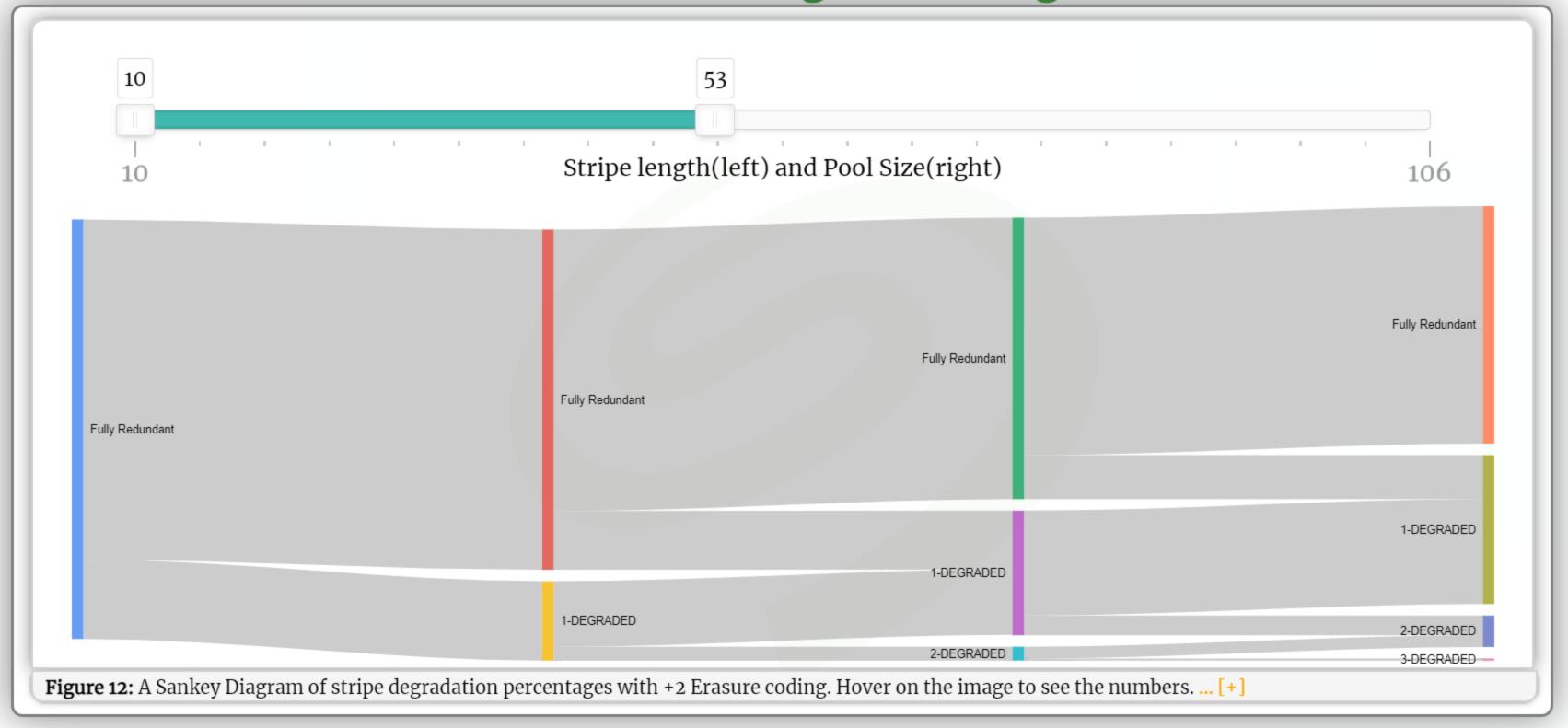


**Figure 11:** An approximate Markov chain for distributed parity of pool size D and redundancy 2. ... [+]

- Consider a system of pool-size D and EC size N, and redundancy c.
  - The overlaps are calculated for D = 53 and N = 8 + 2.
  - Geometric overlap areas scale with powers of N/D.
- Recovery rates:  $\mu_1 \propto D$  and  $\mu_2 \propto D^2$ , failure rate:  $\propto D$ .
  - Increase in failure rate cancels with recovery speed up for c=1.
  - Reli will benefit from ADAPT only if  $c \ge 2$ .
- ADAPT Reli can be expressed in terms of its RAID counterpart:
  - $\mathrm{MTTDL}_{\mathrm{dRAID}} = \left[\frac{D}{N}\right]^{\frac{c(c-1)}{2}} \mathrm{MTTDL}_{\mathrm{RAID}}.$
- For D=50, N=10, and c=2: Adapt reli is 5x better than RAID6 reli.



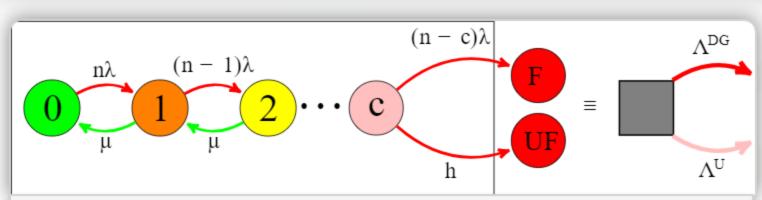
# Visualizing the damage





## Modeling Multi-Layer Erasure Coding

The overall data durability can be improved by implementing another layer of erasure coding. Top layer is composed of already erasure coded sub-elements.

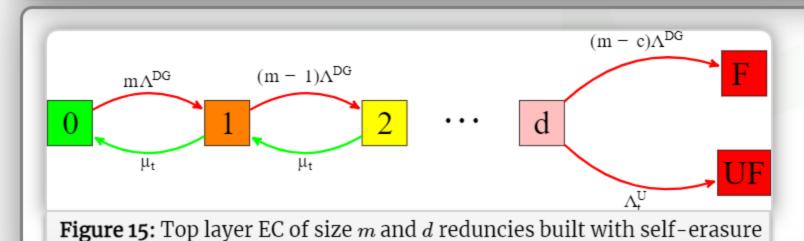


**Figure 13:** Left: the first layer of the overall erasure coding of size n and c reduncies.

Right: A block diagram representation of the erasure coded system as a single element. ... [+]



**Figure 14:** Calm on the surface, but always paddling like hell underneath. A lot of data paddling inside the enclosure, but from outside, it is just a very reliable petabyte drive.



$$rac{1}{ ext{MTTDL}_d^{ ext{t}}} = rac{1}{ ext{MTTDL}_{d, ext{DG}}^{ ext{t}}} + rac{h_{m-d}^{ ext{t}}}{ ext{MTTDL}_{d-1, ext{DG}}^{ ext{t}}}$$

$$ext{MTTDL}_{d, ext{DG}}^{ ext{t}} = \left(rac{\mu_{ ext{t}}}{\Lambda^{ ext{DG}}}
ight)^d rac{(m-d-1)!}{\Lambda^{ ext{DG}} m!},$$

$$h_{m-d}^{\mathrm{t}} = 1 - (1 - \mathrm{UER})^{(n-c)(m-d)C}$$
 probability of URE(s).

- 16+2+Adapt (53-drive-pool) & 7+1 CORTX gives ~13 nines at the overall 73% capacity efficiency(27% overhead).
- ~12 nines can be reached with an 8+5 single layer EC at 62% capacity efficiency (38% overhead).



coded elements.

# **System Availability**

### Availability with no redundancy

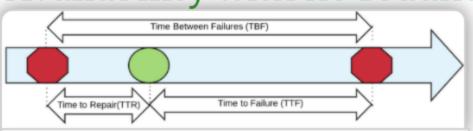


Figure 16: An illustration of the time scales.

- A set of n devices:  $\overline{\text{MTTF}} = 1/(n\lambda_s)$ , and  $\overline{\text{MTTR}} = 1/\mu_s$ .
- Fraction of time spent for repair:  $\frac{\text{MTTR}}{\text{MTTF+MTTR}} \simeq \frac{\text{MTTR}}{\text{MTTF}} = \frac{n\lambda_s}{\mu_s}$ .
- Availability=1-Fraction of time spent for repair:  $A_0 \simeq 1 \frac{n\lambda_s}{\mu_s}$ . (17)

Show a rigorous proof

### Availability with one redundancy

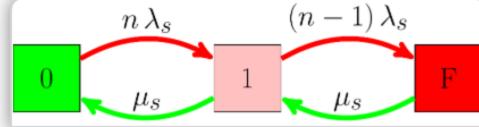


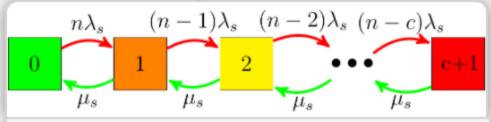
Figure 18: Markov Chain with one redundancy.

- With one redundancy, the data will be unavailable if 2<sup>+</sup> systems are down.
- · Such a system can be modeled with the Markov chain shown on the left.
- The availability can be computed as

$$A_1 = 1 - \left[ n \frac{\lambda_s}{\mu_s} \right] \left[ (n-1) \frac{\lambda_s}{\mu_s} \right]$$
 (22)

Show a rigorous proof

### Availability with c redundancies



**Figure 19:** Markov Chain with  $\it c$  redundancies.

Recognizing the patterns in Eqs. (17) and (22) we can generalize the formula to a system with c redundancies:

$$A_c \simeq 1 - rac{n!}{(n-c-1)!} \left[rac{\lambda_s}{\mu_s}
ight]^{c+1}$$
 (28)





# Appendix

Here we look at the data durability with dual actuator.

Press down arrow to navigate this sections.





# **Durability with Mach2**

Show the GIF

- The reliability of RAID critically depends on the speed of the recovery.
- MACH2 doubles the data transfer  $\implies$  **2x/4x** reliability improvement for RAID5/6.

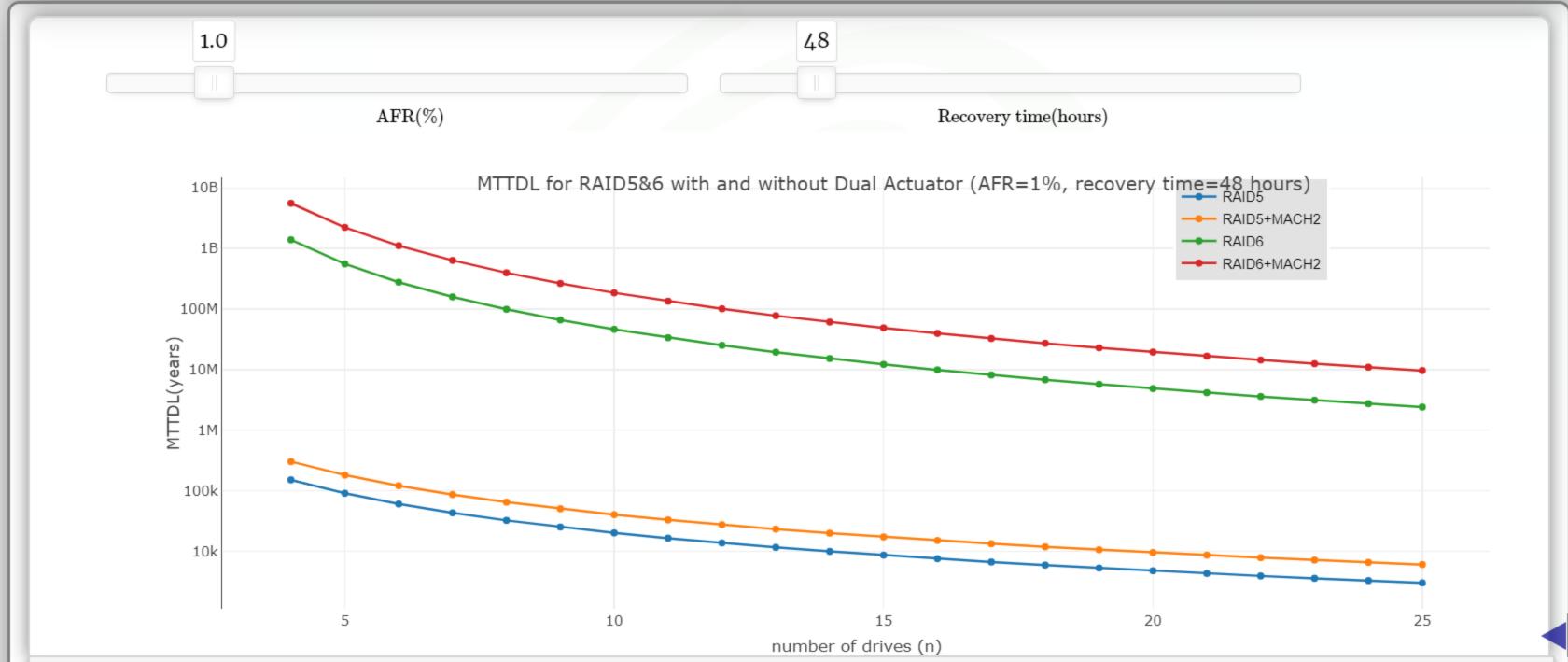
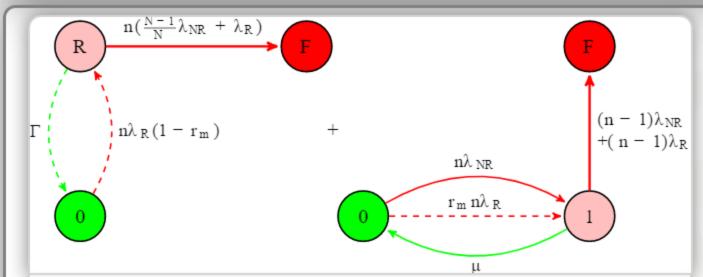




Figure 21: An interactive plot showing the gains with MACH2. ... [+]

# **Durability with ReMAN**

- Consider with the simplest case[14]: one redundancy. Given a head/drive failure, there are two paths to losing data:
  - A second failure while recovering from a head failure: less likely due to faster recovery.
  - A second failure while recovering from a drive failure: more likely due to longer recovery.

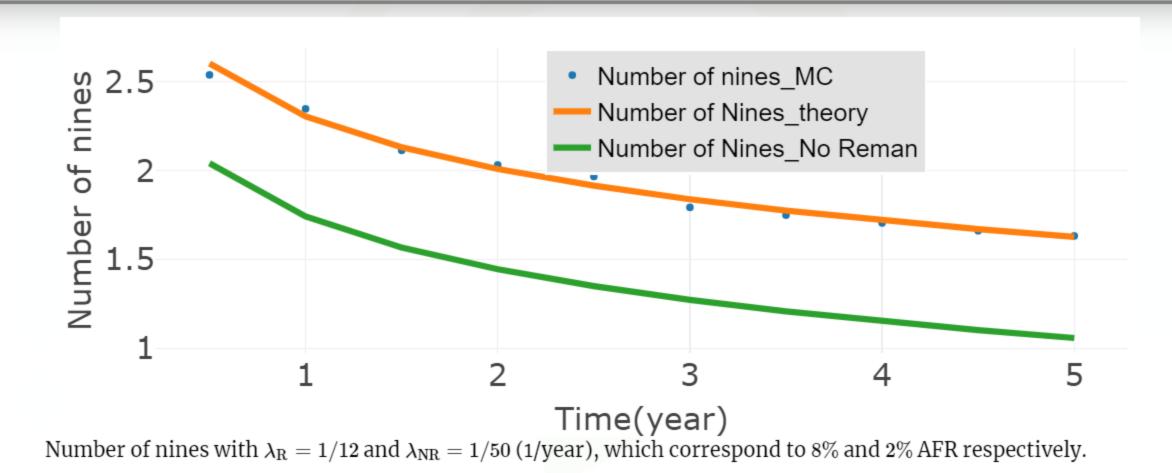


**Figure 22:** Markov chain split into two parallel paths: recovery from subcomponent failures and recovery from device failures.

- The plot on the left shows two parallel Markov chains:
  - Left-most shows data recovery for a ReMan'able failure.
  - Right-most shows the standard recovery when a drive fails.
- $r_m$  term represents the maximally ReMan'ed drive population.
  - ReMan'able failures on maximal drives trigger replacement.
  - This is represented by the dashed red curves.
- The transition rates are time dependent, and involve  $r_m$  functions.
- $\mathcal{R}_1^{(1)}(t) = exp\Big(-rac{\mathcal{C}}{2\Gamma}\Big[t+rac{1-e^{-2\lambda_{\mathrm{R}}t}}{2\lambda_{\mathrm{R}}}\Big] rac{\mathcal{C}}{2\mu}\Big[(1+2\kappa)t rac{1-e^{-2\lambda_{\mathrm{R}}t}}{2\lambda_{\mathrm{R}}}\Big]\Big) ext{ where } \mathcal{C} \equiv n^2\lambda_{\mathrm{R}}^2(1+\kappa), ext{ and } \kappa \equiv rac{\lambda_{\mathrm{NR}}}{\lambda_{\mathrm{R}}}$ 
  - n: number of drives in the EC scheme, N: number of heads per drive,
  - $\Gamma$ : ReMan Repair rate,  $\mu$ : drive repair rate,  $\lambda_R$ : ReMan'able failure rate,  $\lambda_{NR}$ : non-ReMan'able failure rate.
- This is the expression when we allow for 1 ReMan/drive. Similar formulas are calculated for  $R_{max}=2,3$ .
- We have an analytical model of Erasure Coded systems that support ReMan.
- The closed mathematical form can be computed instantly enabling a real-time web application.

## Simulation with online ReMan

- Below is a comparison of Monte Carlo Simulation and theoretical results:
  - ReMan'able AFR= 8% and non ReMan'able AFR=2%.
  - Note that AFRs are take unrealistically high to show the functional behavior.
  - Assuming 1-ReMan per drive is allowed.
- The plot shows the theoretical prediction is remarkably accurate.
  - The gain in durability coming from ReMan is about 4x.





### References

- [1] Y. Xie, Dynamic documents with R and knitr, 2nd ed. Boca Raton, Florida: Chapman; Hall/CRC, 2015 [Online]. Available: http://yihui.name/knitr/
- [2] Hakim El Hattab, Revealjs. 2020 [Online]. Available: https://revealjs.com/
- [3] D. A. Patterson, G. Gibson, and R. H. Katz, "A case for redundant arrays of inexpensive disks (raid)," SIGMOD Rec., vol. 17, no. 3, pp. 109–116, Jun. 1988, doi: 10.1145/971701.50214. [Online]. Available: https://doi.org/10.1145/971701.50214
- [4] L. Hellerstein, G. A. Gibson, R. M. Karp, R. H. Katz, and D. A. Patterson, "Coding techniques for handling failures in large disk arrays," *Algorithmica*, vol. 12, no. 2, pp. 182–208, Sep. 1994, doi: 10.1007/BF01185210. [Online]. Available: https://doi.org/10.1007/BF01185210
- [5] A. G. Dimakis, P. B. Godfrey, Y. Wu, M. J. Wainwright, and K. Ramchandran, "Network coding for distributed storage systems," *IEEE Trans. Inf. Theor.*, vol. 56, no. 9, pp. 4539-4551, Sep. 2010, doi: 10.1109/TIT.2010.2054295. [Online]. Available: https://doi.org/10.1109/TIT.2010.2054295
- [6] G. Wang, L. Xiao-Guang, and L. Jing, "Parity declustering data layout for tolerating dependent disk failures in network raid systems," 2002, pp. 22-25, doi: 10.1109/ICAPP.2002.1173547.
- [7] V. Venkatesan and I. Iliadis, "Effect of codeword placement on the reliability of erasure coded data storage systems," in Quantitative evaluation of systems, 2013, pp. 241–257.
- [8] A. Thomasian and M. Blaum, "Higher reliability redundant disk arrays: Organization, operation, and coding," ACM Trans. Storage, vol. 5, no. 3, Nov. 2009, doi: 10.1145/1629075.1629076. [Online]. Available: https://doi.org/10.1145/1629075.1629076
- [9] T. Kawaguchi, "Reliability analysis of distributed raid with priority rebuilding," 2013.
- [10] W. Padgett, "Weibull distribution," 2011, pp. 1651–1653.
- [11] B. Wilson, "Cloud storage durability," 2018 [Online]. Available: https://www.backblaze.com/blog/cloud-storage-durability/
- [12] B. Beach, "Python code to calculate the durability of data stored with erasure coding," 2018 [Online]. Available: https://github.com/Backblaze/erasure-coding-durability/
- [13] I. Iliadis, R. Haas, X.-Y. Hu, and E. Eleftheriou, "Disk scrubbing versus intra-disk redundancy for high-reliability raid storage systems," vol. 36, no. 1, pp. 241–252, Jun. 2008, doi: 10.1145/1384529.1375485. [Online]. Available: https://doi.org/10.1145/1384529.1375485
- [14] S. Olmez, "Reliability analysis of storage systems with partially repairable devices," 2021 [Online]. Available: Under peer review, available up on request

