ACQUISITION INNOVATION RESEARCH CENTER

Setting Reliability Requirements for Subsystems

INCUBATOR EXECUTIVE SUMMARY AND REPORT

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ACRONYMS AND ABBREVIATIONS

AFMC	Air Force Material Command
AFLCMC	Air Force Life Cycle Management Center
ALDT	Administrative and Logistics Delay Time
CDF	Cumulative Distribution Function
CM	Corrective Maintenance
DoD	Department of Defense
PDF	Probability Density Function
PM	Preventive Maintenance
RDF	Renewal Density Function
RO	Rapid Sustainment Office
USAF	United States Air Force
USC	University of Southern California

EXECUTIVE SUMMARY

Critical defense systems are required to be always available for use. The means for achieving availability goals, meeting needs, and identifying key availability parameters vary across organizations and platforms, making identifying opportunities and areas for efficiency improvements challenging. Although data related to system downtime are captured, they are seldom well-organized and in a form suitable for performing trade studies to identify promising candidate efficiency enhancements.

During this seedling effort, we contacted U.S. Department of Defense (DoD) personnel responsible for system maintenance to discuss their current approach to providing and documenting availability-related issues. Our key finding is that although systems can be significantly different, the means employed and availability concerns are strikingly similar:

- Systems fail more often than expected.
- Systems take longer to restore service than expected.
- Parts needed for repair may not be available and are sometimes borrowed from other systems.
- Some systems get deployed with degraded capability.
- Some systems have internal spares that enable continued use until repairs are possible, but most systems tend to be "single-string."
- Systems occasionally tend to undergo additional repairs found during preventive maintenance cycles.
- Predictive maintenance remains a desired but elusive goal.

Our study examined the potential for using semi-supervised machine learning methods that look for patterns in vast amounts of data. Using synthetic data, we identified and used such patterns to discern availability trends suitable for performing trade studies and evaluating key factors such as costs, risks, maintenance depot efficiencies, and redundancies.

We also created concepts for a trade study dashboard that defines and analyzes availability scenarios. Exemplar scenarios included:

- Depot maintenance time vs. inherent reliability
- Maintenance time outliers
- System usage vs time-to-maintenance
- Redundancy vs time-to-maintenance

BACKGROUND

This Phase I research focused on creating approaches to develop computationally viable metrics to address "-ilities" (i.e., quality attributes) and performance beyond cost.

At the outset, we note that availability is a complicated, mission-dependent concept, and mission needs determine unique availability scenarios. Roughly two dozen availability factors can be traded off against each other within each availability scenario. These factors may have varying degrees of covariance depending on the scenario (i.e., changes in an availability factor may directly or indirectly cause changes in one or more other availability factors).

The Phase I research goal was to uncover availability factors (using a systematic approach), and then begin to understand the impacts of **the** covariance of these factors within a typical availability scenario. The results of this approach are used to construct a framework for balancing availability factors through trade studies. These studies subsequently enable a selection of efficiencies for achieving the needed availability.

Therefore, the primary outcome of our study is the development of a systematic means to evaluate and balance availability factors to optimize one or more of these factors.

This approach can, for instance, minimize upfront costs that achieve a given inherent availability (A_i) possibly at the expense of lifetime costs. This approach could also determine the tradeoff between access to maintenance personnel versus the cost of deploying a more reliable system. Another example, in this vein, involves having trained, readily available personnel versus dispensing with this need by making a more reliable system.

The key tasks involved in this effort were:

Task 1 – Conduct preliminary research

Task 2 – Develop a framework

Task 3 – Create availability scenarios

Task 4 – Explore machine learning algorithms for optimization

Task 5 – Create a preliminary user interface (e.g., notional dashboard)

Task 6 – Prepare a final technical report and briefing, including Phase II overview

TECHNICAL ACCOMPLISHMENTS

After a focused review of the research in this area, the team determined key availability concepts that were used to inform the development and use of the overall tradeoff analyses framework and target availability scenarios. The specific availability concepts of interest include:

- ***Instantaneous availability*** *A(t)*: The probability that a system will be operational at a specific point in time, *t*.
    - Example: a mission needs x types of equipment for an exercise tomorrow; what is the probability that at least x will be operational?
    - *A(t)* could be simply $R^x(\mathrm{t})$ where R is reliability and t is the time "tomorrow"...
    - But should include an evaluation of whether x systems are working correctly since the last repair time, t_r: $\int_0^t R(t-t_r)M(t_r)dt_r$ where M is the renewal density function (RDF), e.g., $M(t) = t + (1 - e^{-at})$
    - RDF defines the probability density function describing 1) the transition from the state when a system is being repaired to when it is operational and 2) the transition from when a system is operating reliably until it needs maintenance, a is the repair rate.

      Point availability is the sum of the above, i.e.,
    - $A(t) = R(t) + \int_0^t R(t - t_r)M(t_r)dt_r$
- ***Steady-state availability*** $A(\infty)$: The long-term availability of a system as time approaches ∞ (after bugs, infant mortality, operator errors, etc., have been worked out).
    - Reflects long-term availability after the bugs, infant mortality, operator errors, etc., have been worked out.
    - While this can be useful, wear-out mechanisms can become a limiting factor as a system ages.
    - For example, older equipment will break down more often than equipment operating in its useful life region.
    - The good news is that the wear-out zone might be relatively far into the future.
- ***Inherent availability*** A_i: This is steady state availability when only corrective maintenance (CM) downtime is considered.
    - and $MTBF = MTTF + MTTR$
    - Note that $MTBF$ may be time-dependent except when the system has achieved steady-state and before wear-out.

- ***Achieved availability*** A_a: Similar to A_i, but includes downtime due to preventive maintenance (PM).
  - » Mean-time-between maintenance: $MTBM = \ uptime/(Number\ of\ failures + number\ of\ PMs)$
  - » $\bar{M}\,(CM\ downtime + PM\ Downtime)/(Number\ of\ failures + number\ of\ PMs)$
  - » $A_a = \frac{MTBM}{MTBM+\bar{M}}$
  - » A_a is among, if not the most, important metric because it accounts for almost all downtime – missing is downtime due to administrative delays, parts backlogs, staffing problems, etc.
- ***Operational availability*** A_o: A measure of the actual average availability over a period of time, including all downtime, such as administrative downtime and logistics downtime.

$$A_o = \frac{uptime}{time\ period}$$

  - » Essentially, this is operational readiness and likely the most important availability metric.
  - » According to the Reliability and Maintainability Engineering Guidebook administrative downtime:
    - ◊ Administrative and Logistics Delay Time (ALDT) is the time spent waiting for parts, administrative processing, maintenance personnel, or transportation per specified period. During ALDT, active maintenance is not performed on the downed equipment.
  - » However, downtime due to administrative and logistics is highly system and organization-dependent.

1.1 AVAILABILITY TRADEOFFS ANALYSES FRAMEWORK

We also constructed a framework that includes mission-specific availability factors. Different availability factors are deemed salient depending on the scenario (supported by the framework). Availability is a multidimensional metric in which the influence of underlying factors depends on the goal of a trade study and the representation used for describing those factors. For example, one goal might be minimizing repair time which might include trading the cost of more maintenance personnel against the cost of more automated diagnosis systems. Another goal could be maximizing the time between outages which could trade implementing prognostic maintenance against less frequent preventive maintenance. Important availability factors include:

- Availability goal (e.g., how much of what type of availability is needed)
- Reliability
- Diagnosability of system components
- Maintainability
- Accessibility of system components
- Minimum mission success criteria (e.g., what is the minimum acceptable performance, i.e., degradability)
- Environmental and usage stressors
- Redundancy and self-repair effectiveness, e.g., fault coverage
- System mass, power, volume
- New system design cost and goal
- System fabrication cost and goal (cost of building and testing a system)
- Lifecycle cost and goal
- V&V costs for new designs
- Acceptable levels of degradation
- Cost of downtime (might be in terms of dollars or possibly in terms of increased personnel risk)
- PM cycles
- Accessibility of spare parts
- Maintenance personnel access time (length of time for maintenance personnel to start working on a system after it is down – preferably as a PDF or CDF)

System age (as in whether it is operating in its useful life or whether it is in its wear-out phase). Tradespace factors are based on the goals and the significance of the factors associated with those goals. Several approaches can be used to sort out the key elements. These can range from simple linear models (e.g., principal component analysis) to transforming values into higher dimensional hyperspace where linear analyses are possible (e.g., kernel trick or similar analyses).

As illustrated in Figures 1-5, the above factors are interdependent, and their covariances depend on the specific system reliability, use, maintenance policy, age, redundancy, etc. We anticipate that the strength of factor dependencies will vary by system and usage, implying that we will need to look at more than simple covariances to determine dependencies. Covariance evaluates the *direction* of dependencies but not the *strength*. Pearson correlation, for example, is one method for measuring the strength of linear relationships between two variables.[1] Another example is Spearman's rank correlation which is a nonparametric measure of rank correlation between two variables.[2]

[1] https://web.stanford.edu/class/archive/cs/cs109/cs109.1178/lectureHandouts/150-covariance.pdf

[2] https://en.wikipedia.org/wiki/Spearman%27s_rank_correlation_coefficient

We anticipate having access to maintenance data in the next phase of this project, which will enable us to determine the Pearson correlations needed for performing trade studies. For example, a trade study might focus on the impact of strengthening or weakening a relationship between factors.

There is a strong interest in pursuing the potential use of predictive maintenance at AFLCMC/RO Rapid Sustainment Office. Predictive maintenance has the potential to reduce unnecessary downtimes by only taking systems out of service when necessary rather than on fixed schedules. Introducing predictive maintenance as a capability adds another "knob" in trade study analyses.

1.2 AVAILABILITY SCENARIOS

Below, we show two-factor availability scenarios illustrating dependencies among key availability factors. The scenarios represent examples of factor strengths in synthetic data. A simple unsupervised learning method (k-nearest neighbors) algorithm shows data point clusters that reflect differences in factor strength.

We anticipate using a semi-supervised method when actual maintenance data are available. Semi-supervised learning labels a cluster from a handful of points within the cluster rather than labeling all points in large datasets. The labeled clusters can then be used in a trade study by comparing new options to each cluster. As we learn more about actual data, we may find that simple clustering methods are not helpful. Still, other learning and prediction options are available, such as deep neural nets, various density estimators, pattern mining, principle component analysis, etc.

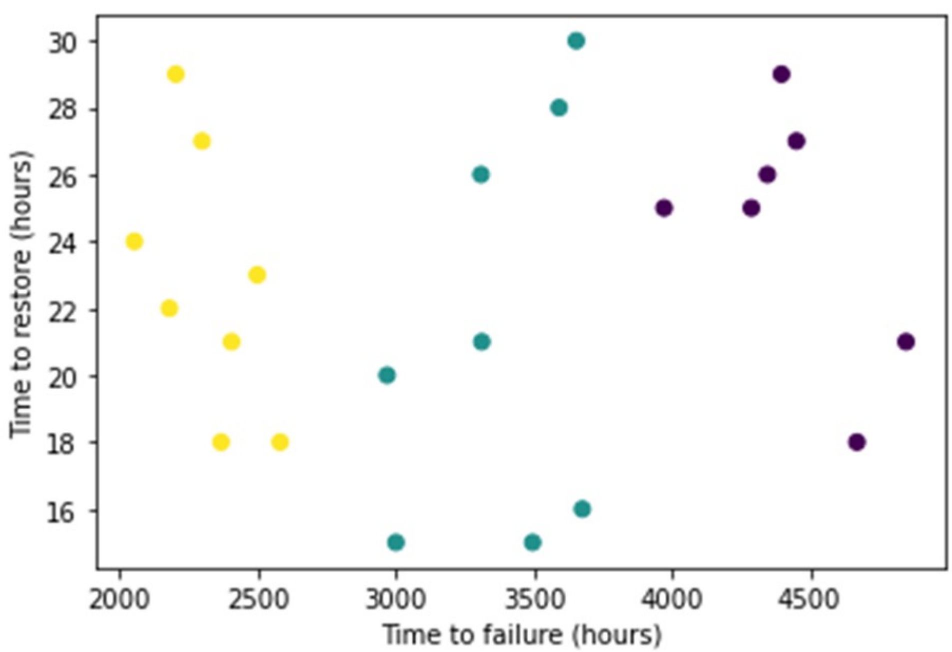

Figure 1. Three Systems in the Same Repair Depot

In Figure 1, the failure rates vary among the three systems, but the time to return the system to service is spread approximately the same, i.e., time-to-restore does not depend on the system.

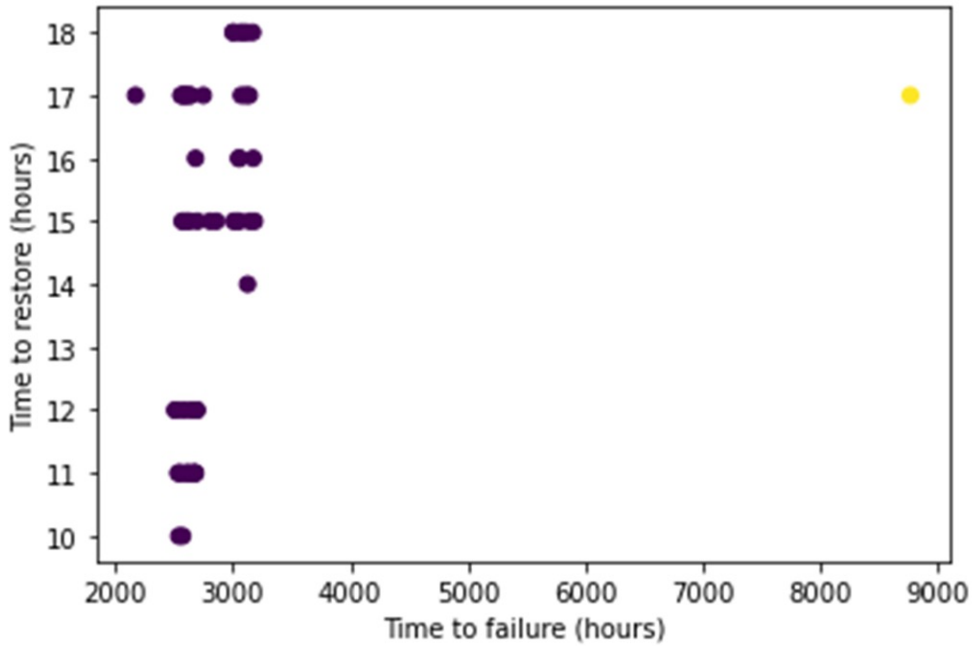

Figure 2. Single System with an Outlier

Figure 2 shows the time-to-failure and restoration time for a single system. Here, the time to failure is relatively constant, and the restoration time falls between 10 and 18 hours. An outlier at 8700 hours needed 17 hours to return to service, indicating that either a maintenance procedure was more complicated than usual, or a required part was unavailable.

As a generalization, this behavior indicates that the restoration time is bounded and not related to the time-to-failure for this system.

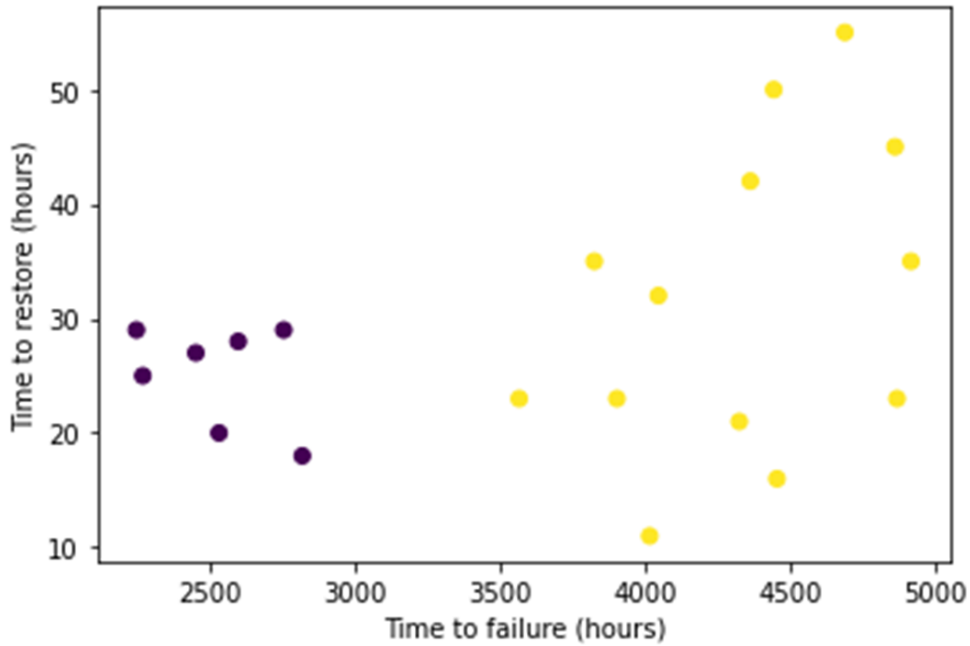

Figure 3. Single System, Different Usages

Figure 3 shows a single system that fails more often in one usage than another. The depot repairing the higher failure rate has a more efficient maintenance team than the second depot.

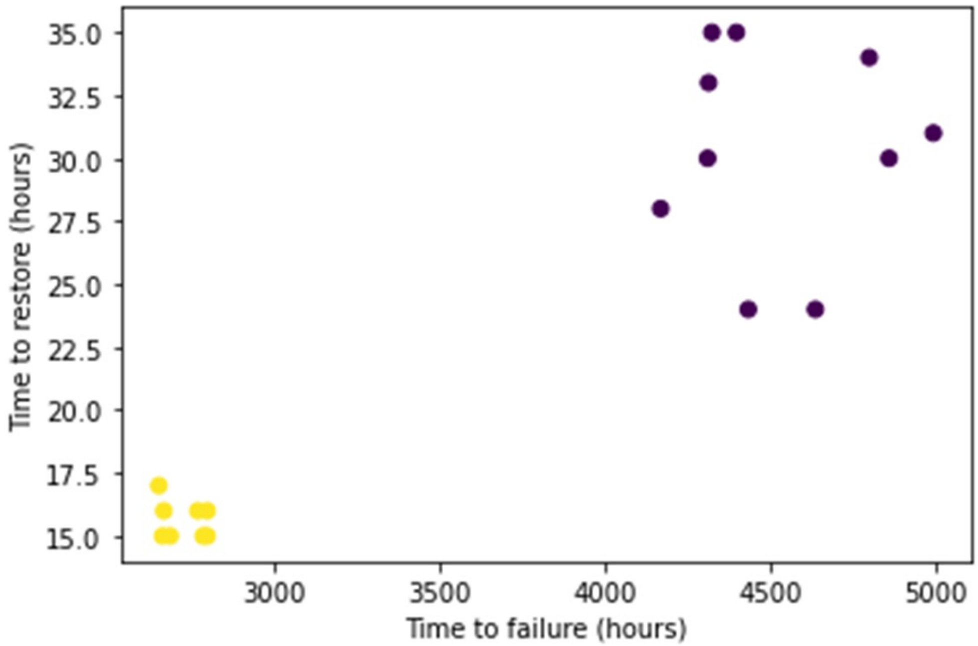

Figure 4. Single System with Quick and Slow Repairs

Figure 4 shows a system with two failure rates in which components that fail often are quickly repaired, while lower failure rate components require more repair time.

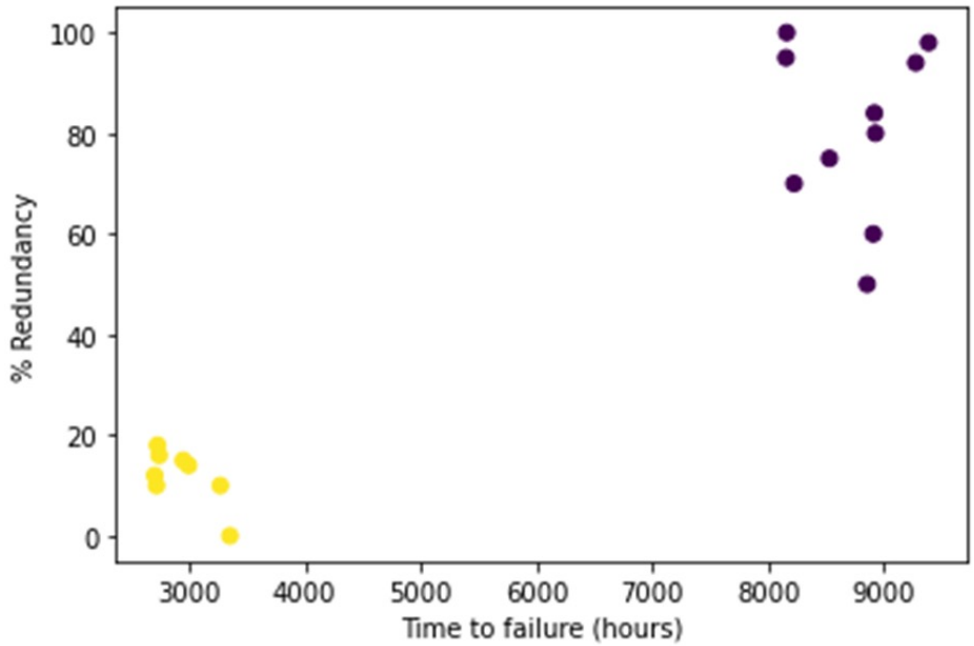

Figure 5. % Redundancy vs. Time-to-Failure

Figure 5 shows how more redundancy can increase the time-to-failure. A trade study needs to explore whether the upfront cost of adding redundancy is beneficial to overall lifecycle cost.

1.3 MACHINE LEARNING ALGORITHMS FOR OPTIMIZATION

In lieu of actual data and given the tight schedule of this seedling project, we created sample datasets, representative of real-world data, to investigate in future data analyses. While these samples do not reflect actual data, they indicate that trade studies may need to account for differences in what components fail within a system, what components need preventive maintenance, and the efficiency of the different maintenance depots.

Internally redundant systems are expected to fail less often than non-redundant systems and, therefore, are expected to have higher availability. In this regard, a trade study needs to explore the cost of redundancy versus the cost of increased maintenance.

Realistically, trade studies involve multidimensional and potentially non-linear data. Standard machine learning and prediction algorithms for high dimensionalities and non-linear data will be employed in a future phase as needed (see references below).

1.4 NOTIONAL DASHBOARD

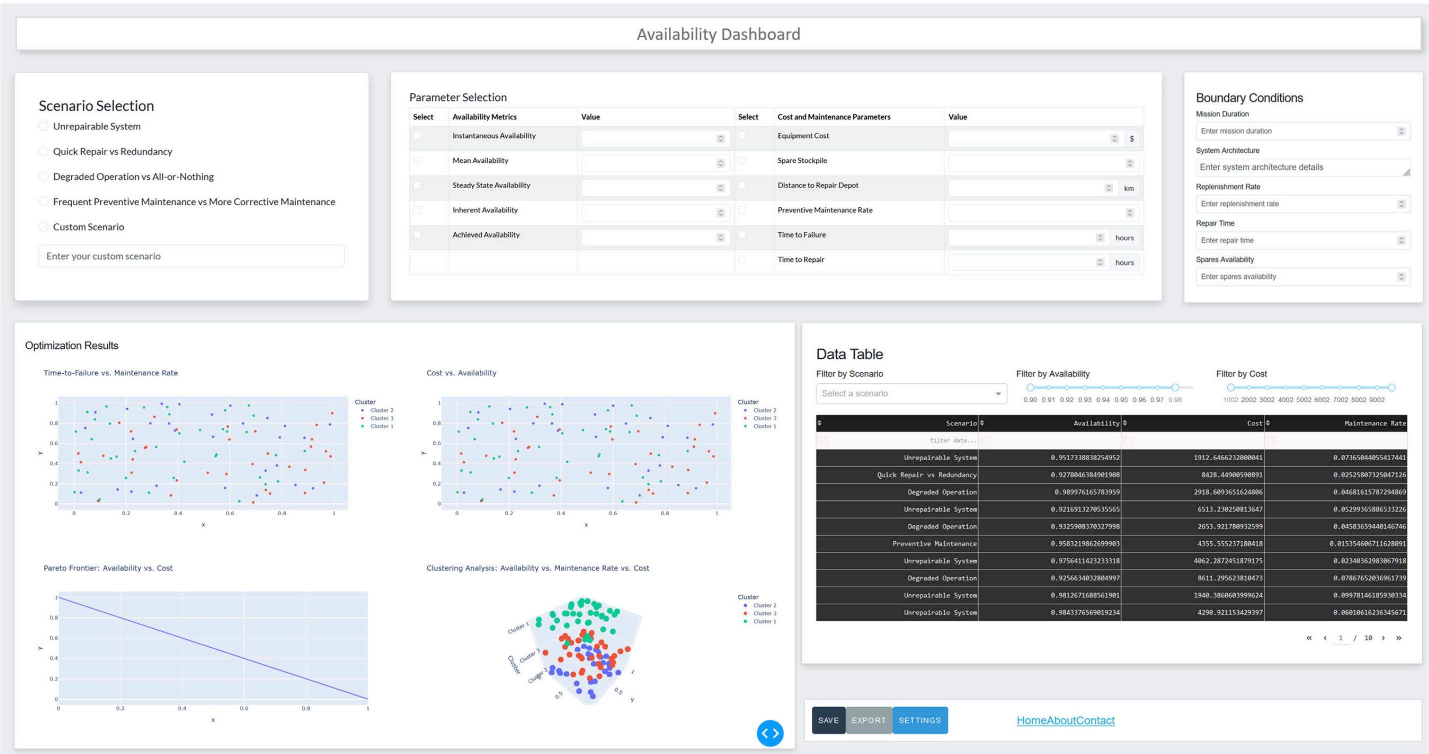

Figure 6. Notional Availability Dashboard

Figure 6 shows a dashboard concept in which an availability scenario is selected in the top left window labeled “Availability Scenario.” Values and ranges of parameters are selected in the Parameter Selection window and limits and constraints are chosen in the top right Boundary Conditions window. The bottom left window graphically displays optimization results, and the bottom right window shows the data used in generating the graphical displays. Users will be able to choose the optimization analysis approach(es), and save and reload scenarios, results, parameters, and graphics.

In a Phase 2 effort, the dashboard will connect to trained datasets, machine learning tools, and commonly used availability algorithms. The dashboard will enable trading off changes to current operational and maintenance procedures and exploring options for future procurements.

Notionally, the dashboard enables the selection of trade space parameters and ranges, maintenance policy, goals, data sources, and constraints. Once the trade is set, the tool generates predictions related to the goal(s) and produces graphics and tables that explain the trade results. We expect the need for multiple prediction methods, which are also selectable in the dashboard.

CONCLUSIONS

The work in this seedling effort was concerned with providing tools for engineers to frame tradeoffs and conduct tradeoff analyses among various aspects of a system design with a view to maximizing system availability. As part of this work, we have also shown the potential for integrating an easy-to-use front-end dashboard with sophisticated backend analysis tools. Importantly, we have several tools in-place that can extract important facts from maintenance records that support explainable results. The team has also contacted two potential sources of actual maintenance data and have been working with these organizations to obtain access for the potential follow-on effort.

Based on this seedling study, we recommend:

- Examining actual maintenance records to determine whether sufficient information is captured that supports predictive maintenance.
- Working closely with our U.S. DoD counterparts to solidify dashboard content, options, scenarios, and needed analyses.
- Developing machine learning tools consistent with available database content.

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