The 64th Annual Reliability and Maintainability Symposium (RAMS), Reno, Nevada, January, 2018

# Using Discrete Event Simulation to Improve Aircraft Engine Reliability Forecasts

Staunton Haynes, NAVAIR

Jeffrey W. Herrmann, PhD, University of Maryland

Paul Zimmerman, NAVAIR

Key Words: aircraft engines, maintenance planning, simulation


*SUMMARY & CONCLUSIONS*

Forecasting engine reliability and subsequent repair demand for maintenance activities (including engine and component removals) is essential to maintaining aircraft availability. These forecasts can be used for financial budgeting, planning human resources, managing facilities, and procuring parts.

Although the current deterministic tools are adequate for mature programs, reliability forecasting for programs in the first years of an engine's life cycle and programs in the last years of engine's life cycle is more difficult due to the acquisition (or retirement) of engines and other changes. A more comprehensive and sophisticated simulation modeling approach was developed to create better forecasts.

Comparisons to historical data show that the simulation model generates reliability forecasts that are as accurate as those generated by current forecasting tools for mature programs. Because the simulation model can represent a wide variety of dynamic scenarios, it is also appropriate for programs in the first years of an engine's life cycle and programs in the last years of engine's life cycle, which will standardize the forecasting process across these programs. Future work will include automated links to build the simulation instances and automated output analysis.


## 1 INTRODUCTION

To maintain the availability of aviation assets, forecasting engine reliability and subsequent repair demand for maintenance activities (including engine and component removals) is essential. These forecasts can be used for financial budgeting, planning human resources, managing facilities, and procuring parts. Inaccurate demand forecasts lead to wasted resources and low availability. The U.S. Navy (USN) is currently using a variety of tools to forecast aircraft engine reliability. Although the current deterministic tools are adequate for mature programs, reliability forecasting for programs in the first years of an engine's life cycle and programs in the last years of engine's life cycle is more difficult due to the acquisition (or retirement) of engines and other changes. A more comprehensive and sophisticated modeling approach was developed to create better forecasts.

Aircraft engines fly a different number of hours each month. The engines have numerous modules, and each module has various components that are susceptible to multiple failure modes. An engine has multiple failure modes with different time-to-failure distributions. Each component has a life limit that restricts the number of hours that it can be used. Each module has a build window such that, if the engine is removed for any reason, and a component's remaining life is less than the build window, then the module is removed, another module is installed, and the low-life components on the removed module are replaced with new ones. If an aircraft needs an engine to replace one that is going to be repaired but no spare engine is available, then the aircraft sits idle until an engine becomes available (and the aircraft's other engine becomes idle as well). Thus, delays in engine repair, due especially to repair shop (maintenance depot) capacity, can reduce aircraft availability.

Current USN engine demand forecasting relies on establishing mean time between removal (MTBR) with historical data. These rates are deteriorated over time using established aging inputs. Likewise, failure rates can be improved over time as a result of engine upgrades and improvement projects. This method presents four challenges that the USN wants to tackle. The first challenge is that deterministic methods such as this result in one answer while the desire is to have a range of answers from which to bound expectations. The second challenge is that failure modes are modeled independently such that an improvement to one failure mode has no impact to any other failure mode. This happens despite a potential increased opportunity for the remaining failure modes to take place. The third challenge is that engineering analysis of failure modes is frequently framed around mean time to failure (MTTF) or mean time to removal (MTTR). This comes from historical removal data as well as performance trend analysis to project future failures. It is difficult to transform that information into MTBR rates in a system level competing failure mode environment without additional probabilistic analysis. Lastly, life limited system components and build windows determine when high time system removals take place. Other failures are typically repaired during these removals. A large MTBR cannot be used to forecast high time removals (due to components that reach their life limits) without considerable additional analysis of fleet life remaining, usage since repair and consideration of failure modes. Given the limitations of these tools, a discrete-event simulation model was considered.

The research team developed, through an iterative development process, a discrete-event simulation model that predicts the number of removals per time period for a set of engines and aircraft. It also predicts the aircraft availability and the number of components consumed. The simulation is a stochastic model; it generates random values for engine time to failure (hours of operation) for each failure mode, the number of hours of operation per time unit for each aircraft, and the times to repair engines and modules. Generating forecasts requires running multiple replications and analyzing the results of these replications to create confidence intervals on the relevant measures.

Meng Xu and Getachew Degefu identified some of the papers cited in this report, and Meng Xu also assisted in programming and debugging the simulation model.

## 2 RELATED WORK

Forecasting aviation maintenance requirements is a critical planning activity due to the need to have the resources required to maintain the availability of valuable aircraft. For example, Yoon and Sohn [1] used observed failures to estimate the parameters of a module's time to failure distribution and then forecast the demand for minor parts at each failure and over longer time periods. Foote [2] used statistical techniques to develop the distribution of demand of aviation spare parts from historical data.

Van den bergh et al. [3] classified aircraft maintenance tasks by extent (light vs. heavy) and uncertainty (scheduled or unscheduled) and reviewed previous work on the operational aspects of aircraft maintenance, including studies that used simulation models for maintenance scheduling (cf. [4]). For example, Mattila et al. [5] described a simulation model that was developed to evaluate the impact of the maintenance resources, policies, and operating conditions on the availability of the fighter aircraft fleet in the Finnish Air Force. (They also listed other simulation studies which are not included here due to space constraints.) Wang et al. [6] used an analytical model to predict the number of failures in a fleet of gas turbine auxiliary power units based on their virtual age (use since last repair).

Forecasting maintenance requirements is a challenge in many industries. Boylan and Syntetos [7] reviewed methods for forecasting demand for spare parts, including methods based on the events that cause demand and time-series methods that use the history of spare part demand, and classified demand patterns.

The problem addressed by this work is similar to the machine interference problem, in which multiple repairmen service machines that can fail, and one is interested in the predicting the number of machines that are working and the rate at which they fail. Stecke and Aronson [8] surveyed the literature on this important problem in 1985. Haque and Armstrong [9] reviewed work since 1985 and categorized it based on the queueing models and other model features such as server availability. Shekhar et al. [10] reviewed more recent work on the machine interference problem.

The model described in this paper has some similarities to the previous models but includes aircraft, engines, modules, and components and details required for the specific goals of forecasting aircraft availability, repair activities, and spare part demand.

## 3 SIMULATION APPROACH

This section describes the simulation model that was constructed. It was developed in an iterative manner so that potential users could experiment with the simulation model, help find flaws, and identify the most important features that needed to be added.

The model, which we call the "Engine Simulation," is a stochastic discrete-event simulation and is implemented in MATLAB. The key events in the model correspond to the following types of activities: an engine begins service, fails, begins repair, finishes repair, becomes a spare, and becomes idle. In some cases, if no spares are available, an aircraft may sit idle, in which case the other engine(s) on that aircraft will become idle. In addition, aircraft and engines can be procured and retired. (A detailed description of the events and states is beyond the scope of this paper.)

The model tracks the states of aircraft, engines, modules (parts of an engine), and components (installed in modules). An engine can be upgraded, which changes the distributions of the failure times for its failure modes.

### 3.1 Input Data

This section describes the data required to instantiate the simulation model.

The input parameters: the length of the simulation run, the number of failure modes, the number of repair levels, the repair level for each failure mode, the repair time distribution by failure mode, the capacity of each repair level (number of engines), the number of engines per aircraft, the probability that an aircraft is inactive in a time unit (month), and the spare engine priority rule.

For each aircraft, its identification number, acquisition time, and retirement time.

For each engine, its identification number, the assigned aircraft, age in hours, number of shop visits (repairs) already done, number of scheduled upgrades already done, acquisition time, retirement time, whether the engine is in repair at the start of the simulation (and repair completion time), and the times at which the engine will be upgraded.

For each type of module, the modules of that type, the build window (hours), the time to repair distribution, the repair level, number of components, and type for each component.

For each module, its identification number, module type, assigned engine, number of shop visits (repairs) already done, and acquisition time.

For each type of component, its life limit (hours) and time to repair distribution.

For each component, its identification number, the assigned module, component type, age (hours), and remaining life (hours).

For each time unit (month), the minimum and maximum flight hours for each aircraft.

For each engine failure mode, by number of shop visits and number of upgrades, the time to failure distribution.

For each upgrade, the distribution of the time to complete the upgrade.

### *3.2 Output Data*

The Engine Simulation yields detailed data for each aircraft, engine, and module and calculates summary data as well, including the following items: (a) the number of component replacements by month and component type, (b) the state of each engine at end of each month, (c) by engine and month, the engine hours run in each month and the time since last repair (TSR) (in engine hours) at the end of the month, (d) the number of repairs started in each month by failure mode, (e) the number of primary and secondary module removals in each month by module type, (f) a log of all failure events, (g) a log of module swaps, (h) the availability of each aircraft, (i) the number of engines in repair at any time, (j) the number of modules in each state at the end of each month, (k) the number of new components installed on each module by month, (l) the state of the aircraft at the end of each month, (m) the number of engines needed by grounded aircraft at the end of each month, and (n) the average time that engines wait to begin repair at each repair level.

For statistical purposes, the user can run the simulation model multiple times and summarize the results over these replications [11].

## *4 EXPERIMENTS*

To show that the simulation model generates accurate reliability forecasts, we designed and performed a series of experiments and compared the simulation model results to the results generated by current forecasting tools for USN programs.

### *4.1 Scenarios*

Two scenarios were generated using different USN engine fleets “A” and “B” to compare baseline forecasts and forecasts where failure modes or life limits were improved upon. Scenario A represents an engine fleet with failure modes that are dominant over life expiration removals. Scenario B represents an engine fleet that is frequently limited by high time removals rather than unscheduled failures.

Michael Kravitz of NAVAIR, set up and ran scenario B forecasts. He also contributed to the evaluation of the simulation model.

### *4.2 Experiments*

For each scenario baseline, the Engine Simulation model ran assuming no improvements were made for comparison to pre-existing deterministic forecast baselines. In scenario A, the dominant failure modes are being addressed through component changes during the next engine removal. Updated failure distributions were incorporated into the simulation at the next engine shop visit for comparison to the deterministic improvement forecast. In scenario B, life limits for each component were increased to reflect updated engineering analyses. These new limits were applied immediately in the simulation which mirrors how they will be applied to the fleet. In this scenario, one of the most limiting component lives was not updated as the engineering analysis is not complete and so the impact to overall engine removals was expected to be muted.

The Engine Simulation results were collected for each fleet scenario and analyzed by averaging multiple forecast iterations. This was done in terms of MTBR, MTTR, Engine Removal and Component Removal where applicable.

Another scenario regarding engine availability was also run on fleet A to understand fleet engine repair turn-around-time (TAT) and engine repair capacity (WIP) constraints in relation to engine availability goals.

### *4.3 Benchmarks*

For these scenarios, the current deterministic forecasting tools we used to predict removals. These forecasts are updated on an annual basis and the most recent updates were used in comparison to Engine Simulation results. Additionally, actual fleet MTBR trends were compared to scenario B as a test for validity.

## *5 RESULTS*

After running the simulation model, the results were analyzed and compared with the predictions from the current forecasting tools.

The engine fleet “A” discrete-event simulation baseline scenario was comparable to the deterministic forecast MTBR. The results were comparable because additional probabilistic efforts were undertaken outside of the deterministic forecasting tool to provide a more accurate result. The improvement forecast divergence seen in Figure 1 is due to the deterministic forecast’s inability to account for an increased chance of failure to other failure modes when one mode is eliminated or improved. No additional analysis was undertaken to counteract this deficiency in order to highlight the drawbacks of the deterministic forecasting tool. (To protect sensitive information, these figures show only relative values.)

The discrete-event simulation does account for failure mode dependencies using competing failure mode distributions and so the results were less optimistic and more accurate. The discrete-event simulation showed a more accurate prediction of future engine MTBR than the deterministic forecast.

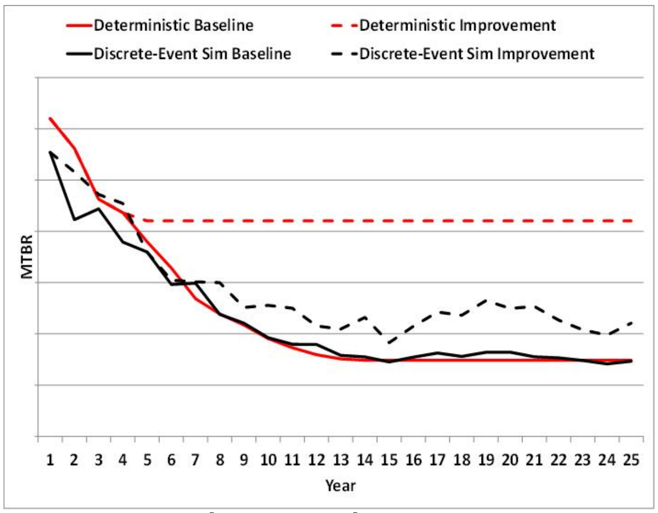


*Figure 1 - Engine Fleet A MTBR by Year*

The deterministic forecast does not output MTTR, but the discrete-event simulation has that capability built in. The result of doubling the time at which one dominant failure mode takes place and eliminating the only other dominant failure mode in this improvement scenario was a 20-30% improvement to the engine MTTR (Figure 2). It also resulted in a 19% reduction in forecasted engine removals due to all causes over the length of the forecast compared to a 59% reduction in removals indicated by the deterministic forecast. If a failure mode was completely eliminated that accounted for 59% of all engine removals, it is likely that other failure modes or high time removals would increase their frequency in its place.

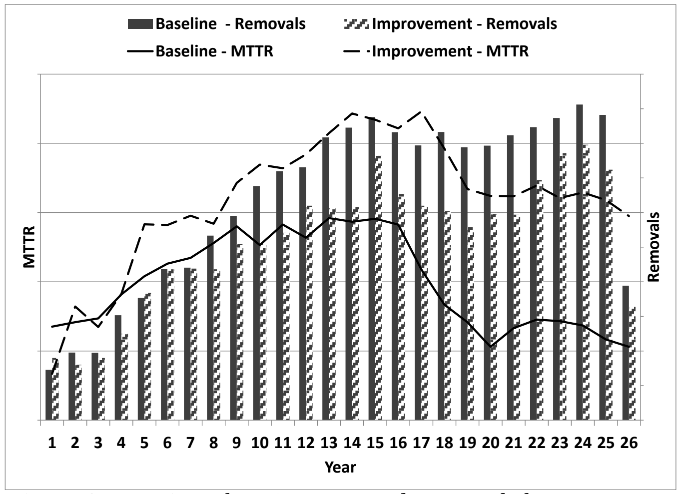


*Figure 2 – Engine Fleet A MTTR and Removals by Year*

Fleet availability was also tested using the discrete-event simulation tool. Comparing a normal engine repair turn-around-time (TAT) to one twice as long and also a normal simultaneous engine repair capacity (WIP) to one half as capable gave us an idea of our trade space for what can happen before we will potentially see installed engine non-availability (Figure 3).

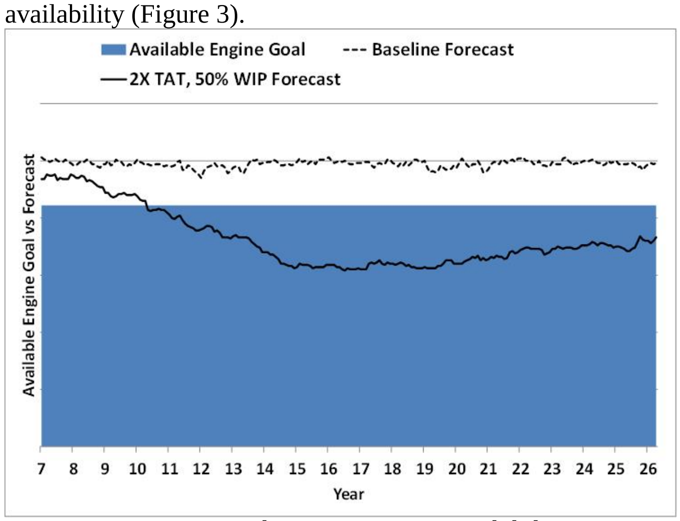


*Figure 3 - Engine Fleet A Engine Availability Forecast Scenarios*

The engine fleet “B” discrete event simulation baseline and improvement scenarios both diverged from the deterministic forecast scenarios. The starting points were similar for each outcome in both tools as well as the actual fleet MTBR trend. After that point, the values diverged with the deterministic forecast over-predicting unscheduled engine removals. This over-prediction was attributed to the tool’s inability to account for competing failure modes and the impact of increasing the opportunity for those failures to happen. This increased opportunity was created by reducing high time removals through life limit expansion. By using a discrete-event simulation with competing failure modes and component life tracking, we were able to forecast a more accurate number of engine removals than possible with MTBR rate based high time removals in the deterministic forecast. The MTBR results in Figure 4 highlight the differences between the two methods.

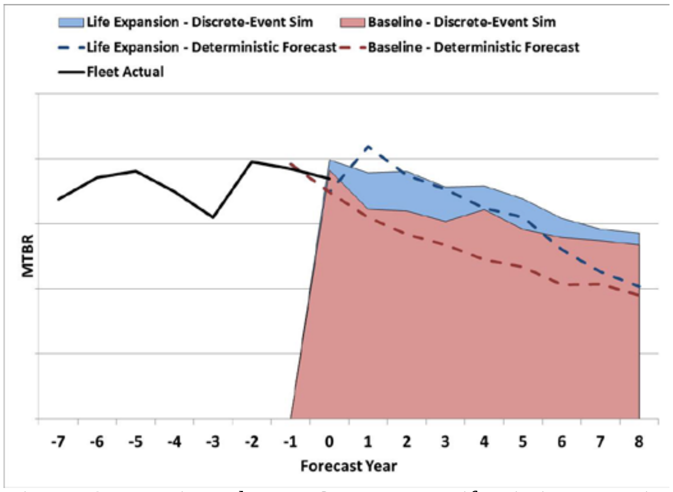


*Figure 4 – Engine Fleet B Component Life Limit Expansion Scenarios: MTBR Forecast*

The discrete event simulation results before and after life limit expansion showed a 21% decrease in engine removals due to the life limit expansion. This makes sense given the frequency at which the engine is removed for high time, the average failure time and the expanded life limits. Engine components were removed 65% less with the expanded limits when comparing baseline and improved discrete-event simulation results. The large disparity between component and engine removals is reasonable given the fact that the most life limited component did not get a life expansion in this analysis and also because engines allowed to fly beyond previous lives will experience more unscheduled engine removals due to the competing failure mode distributions built into the simulation.

### *5.1 Forecast Accuracy*

The predictions from the simulation model and the predictions from the current deterministic forecasting tools were similar. It was noted in one baseline forecast and both improved forecasts that, as the fleets aged, the predictions diverged. This divergence was caused by the deterministic forecasting tools inability to account for mixed failure mode dependencies. An improvement to or deterioration of one failure mode will change the likelihood of other failure modes taking place in the discrete-event simulation while it cannot in the deterministic forecasting tool. Using failure distributions, the discrete-event simulation can better account for these changes while the current deterministic forecast cannot account for the changes without manual intervention.

Additionally, the ability of the discrete-event simulation to track life remaining on individual engine components allowed for more accurate high time engine removal forecasts as well as previously unavailable component removal forecasts.

### *5.2 Computational Effort*

The simulation model took approximately two minutes to run a forecast iteration with a few hundred engines and ten to twenty tracked components per engine. A forecast with a few thousand engines and ten to twenty tracked components per engine took as long as 15 minutes to complete a single iteration. These times can be significantly reduced by disabling some summary calculations depending on what outputs are necessary in the analysis being performed.

Current forecasting tools are deterministic and run in a matter of seconds. Each iteration of the Engine Simulation takes longer than an entire deterministic forecast to complete its calculations. Deterministic forecasts often require additional analyses outside of the forecasting environment to manipulate the results for a more accurate outcome. Those additional considerations have been built into the engine simulation to allow for a standardized approach which is faster to set up, repeatable and has consistent input requirements. The benefits of those additional considerations handled in the Engine Simulation outweigh the additional time required to run each iteration. Further, future Engine Simulation development will include the addition of automated analysis of multiple iterations to significantly reduce the time to analyze results.

All simulations were run on a system with 8GB of RAM and a 2.6 GHz quad core processor.

## *6 DISCUSSION*

At present, the discrete-event simulation provides more information than the deterministic forecast. MTTR, module and component removals, and engine availability are the main additional capabilities that the discrete-event simulation provides. It also manages failure modes as distributions which compete with each other as well as component life limits while the deterministic forecast is based on rates which are independently adjusted over time. The deterministic forecast requires additional external analysis to properly account for the removal or addition of a failure mode and can forecast only high time removals based on an MTBR rate input.

The discrete-event simulation requires each modeler to have an understanding of the distributions they wish to use in the forecast and an understanding of how to properly fit distributions using failure and suspension data. This requires training and a time commitment to set up the forecast. The simulation also requires a significantly larger amount of information about individual aircraft, engines, modules and components at a serial number level in order to function.

The deterministic forecast uses less information; it does not need information for each serial number. Information is being weighed and considered with less detail in the deterministic forecast. Because of this, the results often tend to be less accurate unless significant additional analysis is done to account for non-rate based factors such as high time removals. Additional analysis is also needed to account for the elimination and introduction of failure modes and the impact on other failure modes.

Given unconstrained resources and adequate input data, the discrete-event simulation is more accurate than the deterministic forecasting tool currently being used. It also includes additional information that can be used to understand future fleet MTTR, cost of component replacement and fleet availability.

## *REFERENCES*


1. K.B. Yoon, S.Y. Sohn, "Forecasting both time varying MTBF of fighter aircraft module and expected demand of minor parts," *Journal of the Operational Research Society*, 2007, pp. 714-719.
2. B.L. Foote, "On the implementation of a control-based forecasting system for aircraft spare parts procurement," *IIE Transactions*, 1995, pp. 210-216.
3. J. Van den Bergh, P. De Bruecker, J. Belien, J. Peeters, "Aircraft maintenance operations: state of the art," November 2013.
4. A. Andijani, S. Duffuaa, "Critical evaluation of simulation studies in maintenance," *Production Planning and Control*, 2002, pp. 336-341.
5. V. Mattila, K. Virtanen, and T. Raivio, "Improving Maintenance Decision Making in the Finnish Air Force through Simulation," *Interfaces*, 2008, pp. 187-201.
6. P. Wang, S. Wang, and L. Wang, "Gas turbine APU reliability modeling and failure forecasting," *Reliability and Maintainability Symposium* (RAMS), 2015.
7. J.E. Boylan, A.A. Syntetos, "Forecasting for inventory management of service parts," in K.A.H. Kobbacy, D.N. Prabhakar Murthy, eds., *Complex System Maintenance Handbook*, pp. 479-506, Springer Science & Business Media, 2008.
8. K.E. Stecke, J.E. Aronson, "Review of operator/machine interference models," *International Journal of Production Research*, 1985, pp. 129-151.
9. L. Haque, M.J. Armstrong, "A survey of the machine interference problem," *European Journal of Operational Research*, 2007, pp. 469-482.
10. C. Shekhar, A.A. Raina, A. Kumar, J. Iqbal, "A survey on queues in machining system: progress from 2010 to 2017," *Yugoslav Journal of Operations Research*, 2017.
11. A.M. Law, *Simulation Modeling and Analysis*, Fifth edition, McGraw-Hill Education, New York, 2014.


## *BIOGRAPHIES*


Staunton Haynes
Naval Air Systems Command
Propulsion and Power Engineering
22195 Elmer Road, Unit 4
Patuxent River, MD, 20670, USA

e-mail: staunton.haynes@navy.mil


Staunton Haynes holds an Industrial Engineering degree from West Virginia University. He is employed at the Naval Air Systems Command in Patuxent River, MD where he supports several aircraft platforms by performing engine reliability analysis and forecasts to project impacts to aircraft readiness and engine repair budgets.


Jeffrey W. Herrmann, PhD
A. James Clark School of Engineering
University of Maryland
College Park, Maryland 20724 USA

e-mail: jwh2@umd.edu


Jeffrey W. Herrmann is a professor at the University of Maryland, where he holds a joint appointment with the Department of Mechanical Engineering and the Institute for Systems Research. He is a member of IISE, ASME, INFORMS, and ASEE. Dr. Herrmann is an expert on engineering decision making. He has published 100 journal papers and refereed conference papers and thirteen book chapters, co-authored an engineering design textbook, edited two handbooks, and authored a textbook. In 2003, Dr. Herrmann received the Society of Manufacturing Engineers Jiri Tlusty Outstanding Young Manufacturing Engineer Award. In 2016, his text *Engineering Decision Making and Risk Management* was named the IIE/Joint Publishers Book of the Year.


Paul Zimmerman
Naval Air Systems Command
Propulsion and Power Engineering
22195 Elmer Road, Unit 4
Patuxent River, MD, 20670, USA

e-mail: paul.j.zimmerman@navy.mil


Paul J. Zimmerman is a manager at the Naval Air Systems Command, Propulsion and Power Engineering Department, Reliability Analysis Branch in Patuxent River, Maryland. His 35 year career spans developmental engine testing, engine test cell correlation program manager, engine structural analysis and life management, and establishing the propulsion reliability analysis section that exists today. In 2001 he was recognized in the elite group of Senior Engineers at the Naval Air Systems Command. In 2002 he was awarded the U.S. Navy Admiral Stanley R. Arthur Award for Logistic Excellence. He has co-authored several papers for AIAA and NATO/AGARD. Paul holds an Aerospace Engineering degree from Penn State University.