

IMPACT OF AN AUTONOMIC LOGISTICS SYSTEM (ALS) ON THE SORTIE GENERATION PROCESS

Paul D. Faas

Logistics Readiness Branch
Deployment and Sustainment Division
Human Effectiveness Directorate
Air Force Research Laboratory
Wright-Patterson AFB, OH 45433, U.S.A.

J. O. Miller

Department of Operational Sciences
Air Force Institute of Technology
Wright-Patterson AFB, OH 45433, U.S.A.

ABSTRACT

The current Air Force aircraft logistics system is reactive in nature, meaning that once a fault is detected, maintenance personnel must perform fault isolation procedures and then take steps to repair or replace the faulty item. The Autonomic Logistics System (ALS) concept changes this reactive process into a proactive one. This new approach to the logistics process shows the potential for cost savings, increased aircraft availability, and better system performance. With an ALS, certain logistics tasks can be handled autonomously such as ordering parts for a broken system, calling the right maintenance specialist to the right aircraft, or notifying the maintenance control center that a certain aircraft has a malfunctioning system and will not be available for the next sortie. This study employs an Arena 5.0 discrete-event simulation model to explore the effect of an ALS on the sortie generation process for a fighter squadron during day-to-day operations.

1 BACKGROUND

The Joint Strike Fighter (JSF) aircraft program office is developing a newly emerging operational concept called the Autonomous Logistics System (ALS). The program office is in the system development and demonstration phase of the program with Lockheed Martin as the prime contractor. This new logistics system shows the potential for great savings over the current way the Air Force conducts logistics operations by employing emerging technologies such as prognostics and making use of a distributed information network to accelerate the information flow.

The JSF is not the only program addressing these new technologies; other organizations are investigating this new logistics concept. The Air Force Research Laboratory (AFRL) is investigating whether a prognostics and health management (PHM) system can have a significant impact to the current aircraft fleet. Also, the Army and Navy are

placing a Health Usage Monitoring System (HUMS) on their helicopter fleet (Schaefer 2002).

The heart of the ALS is a fully functional PHM. The PHM detects aircraft system faults, performs on-board diagnostics and fault isolation, and delays maintenance if a system can either be reconfigured or is not required for the next mission. It also relays aircraft status through the Distributed Information System (DIS). The DIS makes PHM data available to all the appropriate logistics functions, keeping them informed of status and making requests for parts, manpower and equipment as the situation dictates.

Rebulanan (2000) constructed a simulation of the basic framework of an ALS (ALSim) as a tool to allow comparison between ALS and the current maintenance process. His model showed that higher aircraft availability could be obtained with an ALS. Malley (2001) focused on enhancing the PHM portion of ALSim. He modeled PHM capability utilizing inputs from notional JSF sensors and employed an artificial neural network to predict remaining service life. Both programs were written in the JAVA programming language with use of SILK simulation classes.

This effort expands upon the framework of Rebulanan (2000) and models the sortie generation process (see Figure 1) for a squadron of F-16s. F-16s are used in the model since there is no available data for the JSF. Data from operational squadrons are used for various model parameters. The model is structured to allow easy insertion of new processes that are deemed appropriate for implementation. As structured our model includes the critical aspects of a base level ALS. This design allows comparison between current system procedures and the envisioned ALS.

2 MODEL ASSUMPTIONS

This model simulates the F-16 aircraft sortie generation operations but is scoped to only cover detailed failure and maintenance for the AN/APG-68 radar. The radar consists

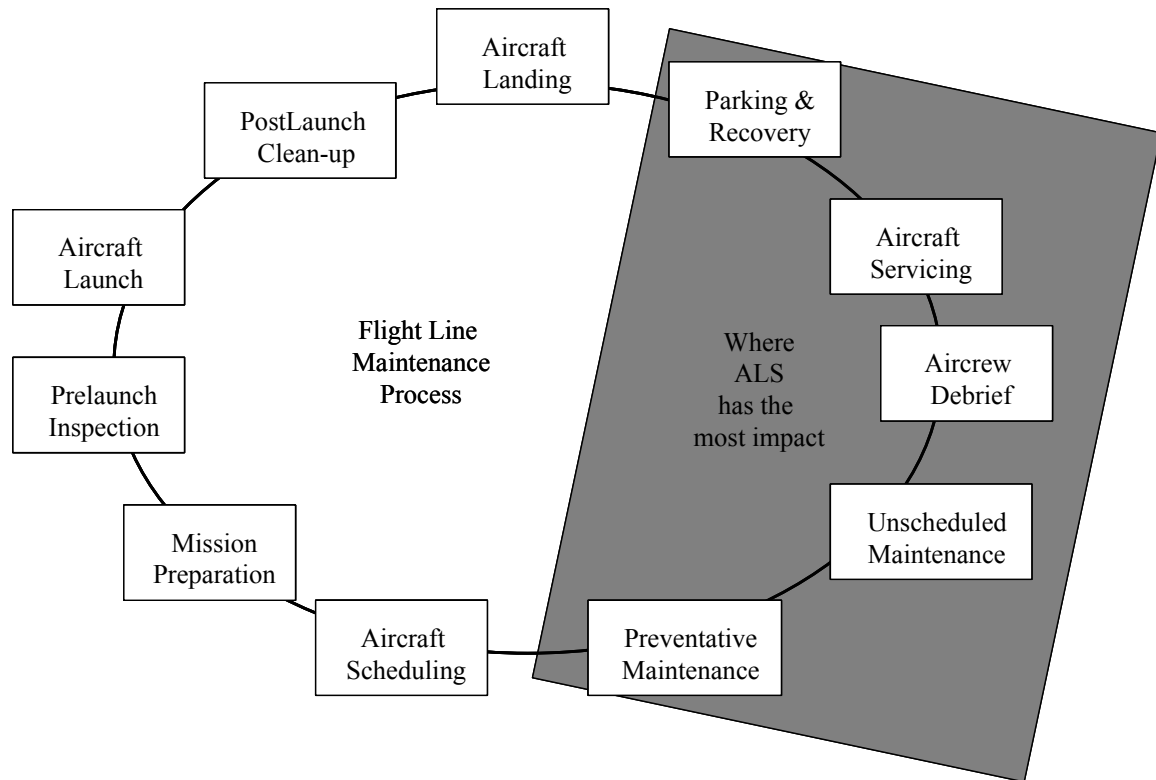


Figure 1: Sortie Generation Process

of four Line Replaceable Units (LRUs): antenna, modular low power radio frequency, dual mode transmitter, and advanced programmable signal processor (Castrigno 2002). These LRUs are abbreviated ANT, MLPRF, DMT, and APSP respectively in the model. A portion of the data for this research was obtained from the Reliability and Maintainability Information System (REMIS) database maintained by Air Force Material Command. It was compiled over a two-year period examining F-16 failures at Hill Air Force Base (AFB), UT.

Other aircraft subsystems are modeled to experience failures at preflight inspection, where they fail per a percentage of scheduled sorties. When these other systems fail, troubleshooting, testing, and documentation maintenance tasks are carried out but no parts are removed/replaced or spares ordered.

The entire supply system is not modeled explicitly, but the delivery of parts (for the four radar LRUs only) from the depot to the flight line is incorporated with appropriate delays and an increase in a counter variable for the specific part. Manpower resources included represent various logistics specialties such as crewchiefs, maintenance specialists, refuelers, and weapon specialists. The model was run with eight refuelers, eight weapons specialists, sixteen crewchiefs, sixteen maintenance specialists for debriefing, and sixteen phase inspection resources available to service the aircraft. In addition, there were four maintenance specialists available to repair the aircraft during scheduled or unsched-

uled maintenance. These numbers are not typical base manning levels, but provide a reasonable pool of resources since the focus of this effort was to measure the ability to produce sorties and increase aircraft availability with the ALS system without considering the impact of manpower usage. A more detailed model considering a wider range of maintenance actions on many aircraft subsystems would require a more detailed modeling of these manpower resources.

Possessed aircraft hours in our model equals the total simulation time. This is true since no aircraft leave flying status (they do not get deployed or sent to the depot). The Mission Capable (MC) rate is calculated by subtracting the not mission capable rates for supply and maintenance. We are only explicitly modeling a single aircraft system (radar system) and how the failures of this system, with or without various ALS configurations, affect our selected measures of effectiveness (MOEs). Therefore, resource levels and other model parameters were selected to obtain a reasonable (approximately 80%) overall MC rate for our baseline model.

The model does not specifically account for the time for not mission capable for both supply and maintenance. The aircraft is either waiting on supply or it is being maintained (maintenance personnel always available with modeled resource levels). The simulation is constructed to run 24 hours a day operations five days a week. Typically each resource only works about 8 hours a day. The weekends are not simulated even though they may be used in the real world to repair aircraft.

3 MODEL DEVELOPMENT

Our model consists of a number of separately constructed functional areas mirroring the sortie generation process in Figure 1. Functional areas include mission preparation, preflight inspection, aircraft launch, flying, landing, parking and recovery, servicing and debrief, failure checking, preventive maintenance, and unscheduled maintenance. Additional areas model the supply process and the logic and procedures necessary to implement the components of the ALS. A GUI is also included to allow the user to easily set 22 different parameters (Faas 2003).

Sixteen aircraft entities initially enter the sortie generation process in the mission preparation area. These aircraft entities flow through the simulation model for the entire replication. At the end of each simulated day, the aircraft are held until the next takeoff cycle the following day. The takeoff times are set by the user at the beginning of the first replication from the GUI and remain constant. The default times are 0800, 1000, 1200, and 1400. The aircraft are released into the next day's cycle four at a time. If an aircraft goes into the preventive maintenance process or is held in unscheduled maintenance longer than a day, that aircraft returns to the hold area after completion of these tasks and then waits for the next scheduled takeoff time.

When created each aircraft entity is assigned an initial time until failure for the four simulated F-16 radar LRUs and

a time since last phase inspection. Time between failures for the LRUs is modeled using an exponential distribution with the means set from the GUI. Once a particular LRU fails and is repaired, a new random draw is taken to set a new failure time. Time since last phase inspection is set by a random Uniform (0, 300 hours) draw for each aircraft. Each subsequent phase inspection for an aircraft occurs 300 hours after completion of the initial scheduled inspection.

Because of the importance of the unscheduled maintenance area of our model, we discuss this area in more detail in the following paragraphs. More information on other model areas not presented here can be found in Faas (2003).

Figure 2 displays the Arena layout for the unscheduled maintenance area. Aircraft entities enter this area from various places in the model. For the baseline system (with no ALS), aircraft enter this area when any LRU fails. With the ALS (PHM flag set), aircraft enter when an LRU's remaining life drops below the PHM preset level (initially set at 10 hours). Aircraft can also enter from the preflight area of the mission preparation area. Entities are routed through unscheduled maintenance based upon how they entered the area.

If replacement of an LRU is required the aircraft is routed to the appropriate LRU area. Here the aircraft first enters a process module that seizes a maintenance specialist and then enters an assign module that reduces the sup-

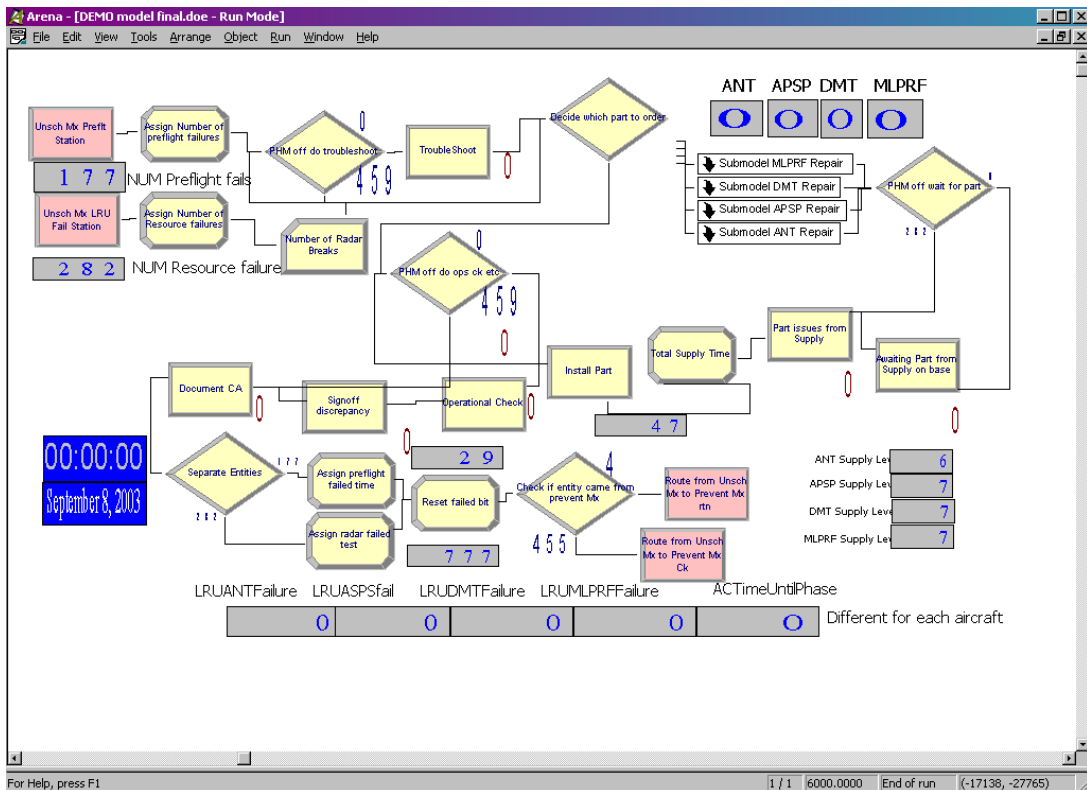


Figure 2: Unscheduled Maintenance Area

ply variable by one. The aircraft then enters a decision module that determines if a part needs to be ordered. This level is set on the GUI with the default to order a part as soon as one is used. If the PHM flag is set, the aircraft entity bypasses the time waiting for the part to be delivered from supply (since we assume the part has already been ordered with the ALS).

4 ANALYSIS

To this point, we have discussed some background on the sortie generation process and an ALS along with some highlights of the development of our simulation model. We now present analysis of our model output for both a baseline system and a system with an ALS. For our ALS system we also examine two factors that significantly affect sortie generation capabilities, the percentage of false alarms and the PHM level as described in the following paragraphs.

4.1 Experimental Design

Our experiment uses MC rate as the response variable in comparing our baseline system (no ALS) to an ALS system, and also examines two controllable ALS system factors, false alarm (FA) percentage and PHM level. Table 1 lists the ALS factors selected and their assigned levels for the planned experiment.

Table 1: Factors and Levels

FACTORS	LOW	CENTER	HIGH
FA (%)	1	3	5
PHM Level (hours)	5	10	15

A FA is defined as the PHM system predicting failure of a healthy part. Within the simulation, aircraft move through a decision module in the flying area and a FA occurs based on a predetermined percentage. This simulates an air abort and one of the four LRUs (FA equally likely for any LRU) is then removed and replaced.

This is a worst case scenario since no further troubleshooting is completed to verify if this was a true fault or a FA.

The PHM level factor is based on the time in hours prior to the actual failure of an LRU that the PHM is able to predict the impending failure. A low setting translates to a more accurate capability in predicting when a failure will occur, allowing an aircraft to get more of the useful life out of an LRU.

The baseline runs show a significant drop off of key output MOEs with FA rates over 5%. Therefore the false alarm rate is limited to 5%. It was also felt that with an operating ALS there would always be FAs, so the minimum percentage is set to one and the center point at three. The baseline runs additionally provide insight into select-

ing PHM levels. The MC rates drop slightly with increasing PHM level. This makes sense since overall LRU life is limited and increasing the time before actual failure when an LRU is removed from the aircraft would decrease the overall life, and in turn the MC rate. However, this will be a trade-off that the ALS designers will need to study since in-flight and unscheduled maintenance hurts flight operations, but removal and replacement too early is more costly. The approach taken for this research set the lowest PHM level at 5 hours to represent the system was predicting failure to an accurate level, with a high of 15 hours and a center point of 10 hours.

4.2 Results

Results were based on a run length of 1250 days (five years with 50 work weeks at five days a week and two weeks dropped for holidays). This run length allowed all aircraft to go through phase maintenance at least once. Thirty replications were run at each design point. Initialization bias was negligible and not an issue with the five year replication length. In conjunction with the selected replication length, 30 replications were used to ensure a reasonable 95% confidence interval half width for key MOEs (2% for each MOE) for our baseline scenario. Figure 3 shows the MC rate for all nine combinations of FA percent and PHM level. This figure clearly indicates that MC rate does not change noticeably across PHM levels for a given FA percentage. However, MC rate drops off significantly with increases in the percentage of FAs. In fact Figure 4 shows with a 5% FA occurrence, the ALS system performs no better than our baseline system.

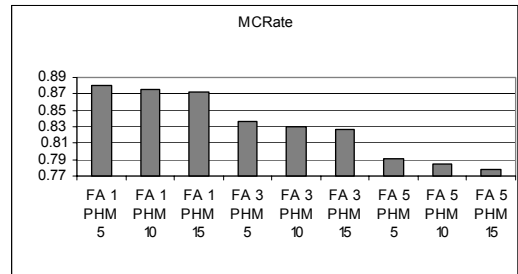


Figure 3: MC Rates ALS Levels

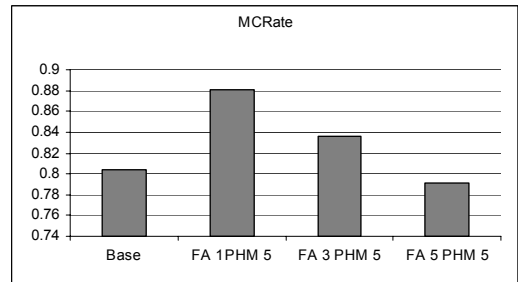


Figure 4: MC Rates Baseline vs. ALS

Table 2 displays the results of an ANOVA performed for the data. With an adjusted R-squared value of 0.982 and a model p-value of less than .0001, we see that False Alarms and PHM level significantly (p-value < 0.0001) affect the MC rate. In addition, their interaction also significantly affects this response.

Table 2: Analysis of Variance Results

Effect Tests for MC Rate					
Source	Npar	DF	Sum of Squares	F Ratio	Prob > F
FA	1	1	0.3708	14435.07	<.0001
PHM	1	1	0.0052	201.5607	<.0001
FA*PHM	1	1	0.0002	7.7457	0.0058

5 CONCLUSION

Our simulation model and analysis investigates the impact of an ALS on the U.S. Air Force fighter aircraft sortie generation process. It should be noted that the specific values reported for our MC rate are not necessarily representative of actual sortie generation capabilities since we are only explicitly modeling a single aircraft system. However, the improvements in the MC rate with the introduction of the ALS, and sensitivities of this rate to variations in the ALS parameters, are representative of the kinds of impact we anticipate with a fully operational ALS.

The results presented show that an ALS equipped fighter squadron can perform better than a non-ALS squadron. Analysis shows an 8% improvement in MC rate from the baseline to the best factor combination for the ALS factors (lowest false alarm percentage and most accurate PHM level). The false alarm affect on the MC rate was most interesting and a little surprising. Taking into consideration that our model provides most likely the worst-case scenario, (part removal with every false alarm), it still provides an interesting example of an area of concern for the PHM designers.

DISCLAIMER

The views expressed in this document are those of the authors and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government.

REFERENCES

Castrigno, J., B. Gilmatrin, J. Bala, and G. Rovnack. Draft Predictive Failures and Advanced Diagnostics Delivery Order 0001 Final Report 29 May 2001.

Faas, Paul D. *Simulation of Autonomic Logistics System (ALS) Sortie Generation*, Thesis AFIT/GOR/ENS/03-07, March 2003.

Malley M., *A Methodology for Simulating the Joint Strike Fighter's (JSF) Prognostics and Health Management System*, Thesis AFIT/GOR/ENS/01M-11, March 2001.

Rebulan, R. *Simulation the Joint Strike Fighter's (JSF) Autonomic Logistics System(ALS) Using the JAVA® Programming Language*, Thesis AFIT/GOR/ENS/00M-19. March 2000.

Schaefer, C.G. and D. J. Haas. *A Simulation Model to Investigate the Impact of Health and Usage Monitoring Systems (HUMS) on Helicopter Operation and Maintenance*. American Helicopter Society 58th Annual Forum, Montreal, Canada June 11-13 2002.

AUTHOR BIOGRAPHIES

PAUL D. FAAS is a government civilian employed at the Logistics Readiness Branch, Deployment and Sustainment Division, Human Effectiveness Directorate, Air Force Research Laboratory, Wright-Patterson AFB, OH. Paul graduated from Purdue University with a B.S. in Aeronautical and Astronautical Engineering in 1982 and received his M.S. in Operations Research from the Air Force Institute of Technology in 2003. His e-mail address is <Paul.Faas@wpafb.af.mil>.

J. O. MILLER is the Director of the Center for Operational Analysis and an Assistant Professor in the Department of Operational Sciences at the Air Force Institute of Technology (AFIT). A 1980 graduate of the U.S. Air Force Academy, Dr. Miller received his M.S. in Operations Research from AFIT in 1987 and his Ph.D. in Industrial Engineering from the Ohio State University in 1997. His research interests include simulation, combat modeling, and ranking and selection. His e-mail address is <john.miller@afit.edu>.