Our study methodology integrated three distinct models, applied through a systematic evaluation process. Figure A.1 depicts the overlying analysis process and model integration points. Beginning at the upper left-hand corner of the chart, we calculated the peace-time LANTIRN average removal rates to the back shops using form 095 pod logbooks from Moody, Mountain Home, and Elmendorf Air Force Bases. Then, applying extrapolation algorithms, we estimated the wartime removal rates. The underlying premise of these algorithms is that sortie frequency, not duration, drives removal rates. For example, as sortie rates change from one to two sorties per day, the pods removed per sortie increase by about 9 percent, almost completely independent of the sortie length. We assessed option outcomes relative to these predicted removal rates as a basis for our comparative strategic decision space. However, to evaluate wartime removals more accurately, we based our computations (presented in the body of this report) on data collected from the AWOS. Appendix F outlines our findings and recomputed wartime removal rates from this latest operation. We modeled the possible range of these rates using a Monte Carlo simulation in which we varied the mean removal rate randomly in concert with several other probabilistic inputs discussed later in Appendix A.

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1We address future scenario uncertainties by randomly varying the mean values of removal rates, test set productivity, and repair time to account for potentially large swings in our predicted values. The distribution ranges used were based on data collected from operating bases as well as the AWOS. We account for local variations around the mean through a 95th percentile calculation for stockage requirements (shown in the example).
The next set of inputs includes the number and type of aircraft that we wish to model, as well as the type of flying program the aircraft will fly. We assumed aircraft were flying at either peace, surge, or sustain rates. The model automatically selected the appropriate removal rates for the flying program. The model also calculated the number of expected pods removed per day for a given location. The number of pods removed supports several computations in the next module. First, each pod corresponds to an associated distribution for repair hours. These hours are used for personnel, stockage, and support equipment requirement computations. Pod removal data were fed into two separate spreadsheets. One sheet calculated the stockage requirement based upon transportation pipelines, and safety stock requirements. The analyst can also set specific pod availability targets to mitigate systemwide pod requirement shortfalls.
The support resource determination model requires several other inputs before calculations are run. First, pod repair times are randomly selected from a discrete distribution, and CND (“could not duplicate”) times are entered for both targeting and navigation pods. Second, manning per shop, productivity rates, and work schedules are entered. For example, there may be five persons per shop for each of two eight-hour shifts, working at 60 percent productivity.\(^2\) Finally, equipment availability as a function of collocated sets was calculated separately. The analysis included a regression model\(^3\) as well as daily hours of operation and work schedules.

Given these supply-and-demand relationships, the model selects the number of repair strings required and the associated personnel. The model also calculates workspace requirements and the peacetime loading for the pod transportation analysis. Finally, the model predicts the annual direct-labor operating costs for the location specified. Before recording these results and moving on to the next location or scenario, the analyst must verify the in-shop queue constraints in a third model.

The queuing model used in this analysis assumed that pods arrive at the shop according to a Poisson distribution. They can be repaired by multiple test sets depending on shop resource constraints. In this model, the repair time is exponentially distributed. The model output is the expected number of hours a pod would stay in the repair shop before being serviced. The analyst must use this output to determine if queue thresholds have been surpassed. For example, if the

\(^2\)Appendix H discusses the productivity assumptions used.

\(^3\)Because of lack of data on the effects of collocating LANTIRN test sets, we employed a regression curve similar to that developed in an associated RAND report addressing support equipment collocation options (see Eric Peltz et al., *Supporting Expeditionary Aerospace Forces: An Analysis of F-15 Avionics Options*, 2000). The equation used in the LANTIRN models is:

\[
C = 17.82 \times A - 0.00078 \times B + 1.90 \times \ln(B)
\]

where \(A\) = expected single-string availability

\(B\) = number of collocated strings in a shop

\(C\) = average expected available hours per string.

Our Monte Carlo simulation assumed a fixed value for \(A\) per given scenario while randomly varying the expected load on the repair shop, thus driving tester requirements.
queue time is over 20 hours, one may change the hours per shift or the number of strings used in the model. Once all constraints have been met, the results are manually recorded in a tracking spreadsheet and the modeler can proceed to the next set of scenario and location assumptions. When running a scenario simulation with the randomly selected inputs described above, the output is in the form of a probability distribution as shown in Figure 3.7.

COMPUTATION EXAMPLE

An analyst would compute the resources required to support LANTIRN targeting pods on a squadron of 18 F-16 aircraft deployed on a combat mission as follows. The mission profiles we assumed have a maximum sortie rate early in the program (say day 15 of a 50-day scenario). We would then select day 15 upon which to base our resource requirement computations. Now, given a mean wartime removal rate of 0.04 TRG pod per aircraft per sortie per day, the expected number of pods removed on a given day is $18 \times 0.04 = 0.72$ pod. When running the Monte Carlo simulation, the model would generate a distribution of expected pods per day. Next, to compute the number of expected hours required to repair the pods, the model multiplies the number of pods by the expected repair time. Using the mean powered-on repair time for TRG pods, we first compute the total repair time by increasing the on-time by 30 percent to account for powered-off processing. The interim value becomes $13.8 \text{ (hr)} \times 1.3 = 17.94 \text{ hr}$. Next, we must account for processing time when no repair took place or for CND time. This process has a mean time of about 5.5 hr. We also found that about 7 percent of all TRG pods do not need repair. The expected repair time then becomes $17.96 \times (100\% - 7\%) + 5.5 \times (7\%) = 17.09 \text{ hr}$. But before we continue, we wish to account for potential repair-time improvements resulting from upgraded support equipment. Suppose the mean repair-time improvement is 13 percent, then the expected repair time becomes $17.09 \times (100\% - 13\%) = 14.9 \text{ hr}$. Again, our simulation varied repair time and repair-time improvement to yield a probability distribution. Given this mean repair time we now compute the expected load on the shop as $0.72 \text{ pod} \times 14.9 \text{ hr} = 10.73 \text{ hr per day}$. 
Clearly, this example puts minimal loads on the shop, yet we still must compute the minimum resources required. First, to compute personnel requirements, we assume that a minimum of two people are required per shift for every fractional or whole pod expected to arrive in the shop. Because we are modeling a wartime scenario, we set the number of shifts at two, at 12 hours each. So in our case a minimum of $2 \times (\text{round up of } 0.73 \text{ pod}) = 2$ people are required to process the pods. Next, we must modify this number by the expected productivity rate for wartime operation (we used 90 percent). The number of people becomes $2 / 0.9 = 2.22$ direct labor personnel. Now we compute the overhead labor requirements. We start with one supervisor per shift, which in our case equals two. Then we add one shop chief per shop for a total of three overhead personnel.

Before we compute the trainee and supply personnel requirement we must first calculate the number of test sets required for this example. As described earlier, we expect about 10.73 hours of repair time per day. Given a 24-hour-per-day operation, we may expect to have equipment available 24 hours, but this availability must include the expected performance of the equipment. Because daily performance data were not available, we used an average mission-capable (MC) rate metric. Forecasting MC rates is difficult, so we chose a range of possible performance levels (see Appendix B). If we have an MC rate of 80 percent, then the expected available hours per a single tester would be $24 \times 80\% = 19.2$. Next, we would equate this value to the expected workload of 10.73 hours resulting in a requirement for one string. These values are then fed into a queuing model (described earlier) with which the analyst can verify the expected wait time for each pod; in this case it is 12.04 hours. Supporting one tester with upgrades requires about one-half of a full-time person, so now the total shop manning becomes: $2.22$ direct personnel + $0.5$ supply person + 1 supervisor = 3.72 people per shift, or 7.44 people per shop + one shop chief = about 9 people. One can also add trainees to the total manning as a function of the number of test sets available for training.

Finally, we want to compute the spare pods required to support the 18-aircraft squadron. Starting with a removal rate of 0.73 pod per day, we need to decide on an availability goal. In our analysis, we used an 80 percent availability for engaged aircraft. In other words,
we would like to maintain 0.8 good pod for every aircraft. So in our example we would need a minimum of $0.8 \times 18 = 14.4$ pods. The expected number of pods that would typically fill the repair pipeline will increase this figure. Suppose it takes two days to repair a pod and about one day to transport it from the flight line to the repair shop and another day back. The total repair pipeline becomes $2 + 1 + 1 = 4$ days. Next, we compute the number of pods that may be removed during this time: $4 \text{ days} \times 0.73 \text{ pod per day} = 2.92$ pods. To this we add a 95-percent confidence level to account for process variability by computing the square root of $3 \times \text{pipeline} = 2.96$ pods. The total pods needed to fill the pipeline is $2.96 + 2.92 = 5.88$ pods. We now add this figure to the minimum good pods required, for a total of $5.88 + 14.4 = 20$ pods for the 18 aircraft. So the total resources required to support this unit are one test set, 20 pods, and nine people.