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An Evaluation of End of Maintenance Dates for Electronic Assemblies

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Abstract **- The business of supporting legacy electronic systems is challenging due to mismatches between the system support life and the procurement lives of the systems' constitute components. Legacy electronic systems are threatened with DMSMS-type obsolescence (Diminishing Manufacturing Sources and Material Shortages) and the knowledge of their system support lives based upon existing replenishable and non-replenishable resources may be unknown. This paper describes an End of Repair/End of Maintenance (EOR/EOM) model, which is a stochastic discrete-event simulation that follows the life history of a population of parts and cards and determines how long the system can be sustained based upon existing inventories of spare parts and cards, and optionally harvesting of parts off of existing cards to increase system support length. The model includes: part inventory segregation, part-specific degradation of inventories, user-defined inventory inspection periods, and operates from failure distributions that are either user-defined or synthesized from observed failures to date.**

A case study using a real legacy system comprised of 117,000 instances of 70 unique cards and 4.5 million unique parts is presented. The case study was used to evaluate the system support life through a series of different scenarios: obsolete parts with no failure history never failing, obsolete parts with no failure history immediately incurring their first failures, and with and without part harvesting. For this example case with existing inventories, the model indicates for the 'best-case' scenario that the legacy system can be supported for approximately 20 years prior to its first EOM event. The immediate first failure assumption decreases the system support life by two years, while harvesting parts extends the system support life by two years.

Index Terms - sustainment, COTS, legacy systems, demand forecasting, EOR, EOM, harvesting, DMSMS

I. INTRODUCTION

The sustainment of electronic systems is a challenging task for system supporters. This challenge varies from system-to-system and encompasses a large number of factors including the reliability of fielded components, required system availability and supply chain and inventory management, all while trying to minimize system life-cycle costs. In an effort to lower system support and development costs, aerospace electronic systems designers shifted towards the use of commercial off-the-shelf (COTS) products as a substitute for "government unique" components. The introduction of COTS components led to less expensive volume production, 'single source bound' avoidance and increased application flexibility, but brought about its own set of problems [1].

The COTS components create difficulties for many applications--their component reliabilities may not meet the requirements of mission critical systems, required specific operating conditions, and they bound users to volatile market trends where technology continuously evolves [2]. This rapid technological evolution periodically introduces "new and improved" components; however, the evolutionary road creates ripple effects that hinder electronic system supporters. The emergence of electronic part obsolescence (DMSMS-type obsolescence) whereby a component is no longer procurable from its original manufacturer is a problem that plagues many aerospace system supporters. The result of obsolescence inevitably leads to higher system life-cycle costs and becomes a major cost driver in systems that frequently experience long support lives (e.g., military and aerospace electronics systems). The estimated costs for the U.S. Navy due to obsolescence are approximately $750 million annually [3].

The obsolescence problem is typically associated with systems considered "sustainment-dominated"; i.e., systems whose long-term sustainment (life-cycle) costs exceed their original procurement costs [4]. Examples of sustainment-dominated systems include avionics, naval systems, nuclear power plants, air traffic control systems, and medical equipment. Sustainment-dominated systems are low-volume and have long field lives (often 20 years or more) that often require high availability. Sustainment-dominated systems often become legacy systems because it becomes too expensive to replace them. Long-term support of these legacy systems (rather than redesign or replacement) eliminates many potential risks and is often perceived to be less expensive. The focus for system supporters becomes minimizing system life-cycle cost while maximizing system support – this problem is typically resolved through a variety of reactive obsolescence mitigation approaches.

Reactive approaches, although not a solution to the obsolescence problem, provide the supporter with ways to manage the problem tactically. Reactive management approaches include alternate or substitute parts, aftermarket sources, lifetime buys, thermal uprating of parts, and emulated parts [5]. The strategies focused on in this paper are those that use existing stocks (often the result of part lifetime buys) of parts and reclamation to extend system support life based upon currently owned excess components and fielded legacy assemblies.

The model proposed in this paper uses Monte Carlo sampling of part reliability distributions to forecast part demands. These part reliability distributions can either be pre-defined or created on the basis of historical component failure data. The model follows the life history of a population of parts and cards and determines how long the system can be sustained based upon existing inventories of spare parts and cards, and optionally harvesting of parts off of existing cards to increase system support life. The end of system support life (i.e., End of Maintenance) is the earliest time that the inventories fail to support subsequent forecasted part demands. Likewise, the End of Repair date is the last date that the last repair or manufacturing action associated with a part can be successfully performed. The next section describes existing demand forecasting models, followed by sections that present the methodology of the End of Repair/End of Maintenance (EOR/EOM) model, a stochastic discrete-event simulation that forecasts system support life capabilities for legacy system supporters based on existing inventories of spares. The model provides system supporters with probability distributions and associated confidence levels of system support life capabilities, identifies parts critical to the causation of system support loss, and calculates the rate of system support loss due to subsequent failures to meet forecasted demands.

II. DEMAND FORECASTING

Demand forecasting is a crucial issue of inventory management and plays a significant role in electronic systems sustainment modeling. The challenging task is developing a methodology that accurately forecasts part demands based on historical failure data. Demand forecasting of parts to support a system is commonly performed using renewal functions [6,7]. Renewal functions predict the number of renewal (part failure) events in a specific period of time and are a common method used to determine warranty reserve funds. However, renewal functions only calculate the expected number of events in a time period, not their respective dates. Renewal functions and other basic sparing and warranty models are generally confined to calculating renewals for populations of parts represented by a single probability distribution. In order to effectively address the EOM problem, one would have to evaluate each unique population of parts individually (assuming these populations of parts do not draw from the same inventories) and then determine the system support life by finding the earliest time one of the population sets could not be supported.

Croston's method [8] is a common approach for intermittent demand forecasting involving exponential smoothing forecasts based on the size of a demand and time period between demands. However, these methods only provide point forecasts and cannot produce forecast distributions and demand prediction intervals. The demand forecasting problem also requires that the model be able to incorporate random nature, associated with spare parts demand for mission critical systems.

An alternative to these methods is the use of stochastic models to determine future parts demand. A stochastic process allows for a multitude of probable and possible solutions based upon associated uncertainties, allowing for system complexities to be fully and accurately explored. Stochastic models incorporate the inherent randomness associated with spare parts demands, meaning that demands for a part arise only when that part actually fails. The derivation for stochastic analysis of demand forecasting for service parts [9] and approximate model closed-form solutions are proposed for constant part failure rates and constant part discard rates. The proposed stochastic model developed in [9] determines part demands for given periods of time based on periodic product sales and failure information. Eppen and Martin [10] investigate two cases considering stochastic demand size and lead times in a given period where the parameters of the distributions are known and unknown. When the parameters are unknown, they use a simple exponential smoothing model to generate estimates of demand in each period. Both of the presented simplistic stochastic models [9,10] only forecast part demands considering one part type during analysis. Real, systems contain hundreds of parts where each part could be characterized by a different probability distribution characterized by different distribution parameters. The objective is not only to forecast multiple parts demands stochastically and simultaneously, but to track the system support life information (part failures, inventory depletion, and costs) over time as the forecasted part demands occur as 'events' that change the system. The ability to forecast individual part demands is included in simplistic stochastic models, but the manner and organization of how this process is carried out is also of importance and it is not accommodated in the simple models.

In this paper we develop a general solution based on discrete event simulation. We simulate an entire system support's lifetime through the stochastic process of forecasting several part demands (a timeline that progresses through part demands) simultaneously while retaining the ability to track at any instant during the simulation what particular event is taking place (what part fails and when the failure occurs).

III. END OF REPAIR/END OF MAINTENANCE (EOR/EOM) MODEL

The discrete event simulator described in this paper models the process of inventory depletion through system operation for legacy systems and tracks the end of repair and end of maintenance dates for the system. The electronic systems hierarchy assumed in the model includes parts and cards. Parts are synonymous with components and cards are synonymous with assemblies or LRUs. As previously mentioned, *End of Repair* (EOR) is defined as "the date that the last repair or manufacturing action associated with a part can be successfully performed." EOR dates are part-specific and may also be card-specific if the particular card can only draw from certain inventories. Similarly *End of Maintenance* (EOM) is defined as "the earliest date that all available inventories fail to support the demand for one or more specific parts resulting in the loss of system operation." EOM events are caused by a specific part on a specific card.

Part Demand Sampling

Only obsolete parts are considered in demand forecasting within the EOR/EOM model; all the non-obsolete parts are assumed to be continuously procurable as needed. The sampling of the part demands is performed using Monte Carlo, a sampling technique used for obtaining values from probability distributions involving inherent uncertainty. The number of forecasted part demands is proportional to the total number of fielded part instances within the entire system because each part is considered unique within the model and tracked independently using discrete forecasted demands. Sometimes organizations supporting legacy systems are uncertain of what reliability distributions or failure behavior the parts within their system exhibit, but they may have maintenance records for observed part failures. The model can use this historical failure data (number of failures to date and the recorded calendar date of the first failure) to generate a probability distribution for the part. The generated uniform distribution[1] with lower bound a and upper bound b for a particular part with a failure history is given by,

$$a = (D_{FF} - D_S)O_P \tag{1}$$

[1] The methodology does not require the characterization of the failure histories for parts as uniform distributions where each value in the range is equally likely to occur. A uniform distribution is only an example treatment that can be used if no other information is known.

$$b = \frac{(D_A - D_S)O_P - a}{\frac{N_f}{N_t}} + a \tag{2}$$

where,

D_{FF} = calendar year of the first failure
Ds = calendar year the part was fielded
D_A = calendar year of the start of analysis
O_P = operational hours per year
N_f = number of failures to date
N_t = total number of fielded parts within entire system.

The upper boundary of the distribution, *b*, is dependent upon the fraction of failures to date (between the date the part was fielded and the start of the analysis) divided by the total number of fielded parts. When the ratio, $\frac{N_f}{N_T}$ equals 1 (all failures observed prior to the start of the analysis), the upper bound becomes the difference between the start of analysis and the date the parts were fielded. Likewise, as $\frac{N_f}{N_T}$ approaches 0 (no failures observed), the upper limit of the distribution approaches ∞. When $\frac{N_f}{N_T}$ approaches ∞ (a large number of failures relative to the population of fielded parts), the upper limit of the distribution approaches *a*.

The model can also account for parts that have no prior failure history. Obsolete parts that exhibit no failure history are implicitly assumed to never fail during analysis (best-case). The question then is: "What if the parts that have never failed before all of sudden start to fail? How will this affect my system support life?" The model also allows for a 'worst-case' scenario, where 'no-failure history' parts incur immediate first failures just prior to the start of analysis and their uniform distributions are then generated based upon the immediate failure in conjunction with additional historical data.

Discrete Event Modeling Process

The model described in this paper has the ability to track information regarding individual parts from introduction through failure, replacement and possibly subsequent failures and replacements through the system support life until end of maintenance occurs. A process flow is depicted in Fig. 1.

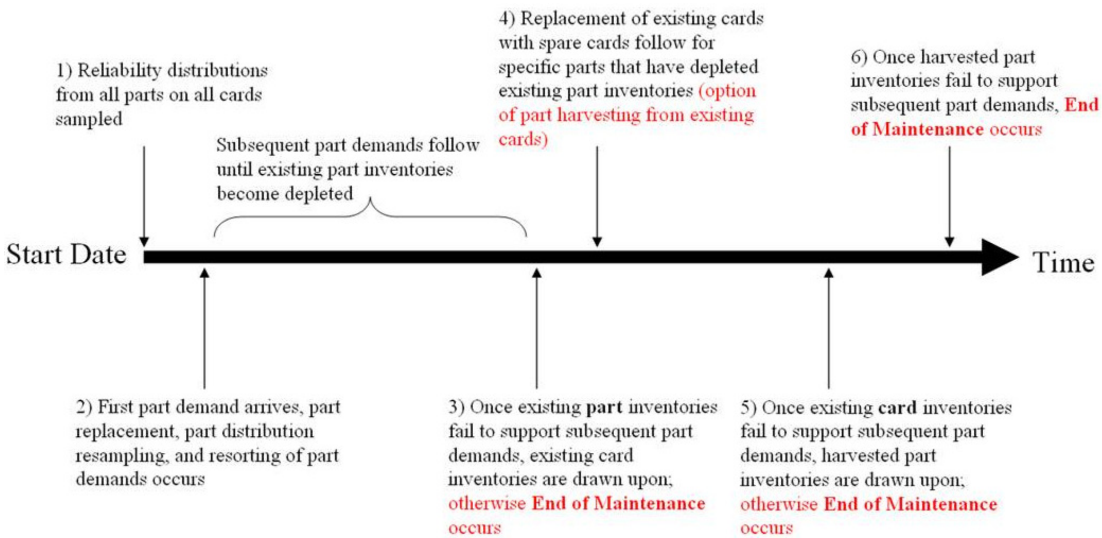

Fig. 1 EOR/EOM part failure process flow

The model starts by sampling the dates of part demands for individual parts that are located on cards within the system. After all of the demand dates are sampled within the system, the demands are sorted from earliest to latest on a part-by-part basis.[2] The model then determines the earliest part demand that occurs in the system, progresses to its date, and performs a change to the system (this type of change is dependent on the type of event that occurs and available inventories). After the change has been applied, the second earliest part demand is found, the model progresses to its date, and the process continues. The model continues until a part demand cannot be fulfilled by existing inventories that previously sustained it (i.e., inventory stock-out).

The simulation begins at the analysis date and the simulation time progresses until an End of Maintenance event occurs (where a part demand cannot be fulfilled by existing inventories that previously sustained it) --this constitutes a single simulated life history of the entire system. In order to provide an

[2] A part is classified as a component specific to a particular card and retains its own unique properties (probability distribution and quantity). Each instance of a part on a card is treated individually (represented by its own forecasted part demand sampled from the part's probability distribution).

accurate representation of the system support life considering part demand uncertainties, multiple system life histories are tracked (typically 1,000) in order to produce probability distributions of End of Maintenance dates and to identify the possible parts/cards (and their associated likelihoods) that cause system support loss.

Determining EOR/EOM Information

End of repair and end of maintenance events are recorded within every simulated life history of the system. The information associated with each of these events is also recorded and analyzed at the end of the simulation. The model has the ability to track multiple EOR/EOM events within a given system life history. These are referred to as "ordered" events, whereby the first-ordered end of maintenance event is synonymous with the first end of maintenance event and so on. The calculated EOR/EOM information that is analyzed is based on the order of occurrences.

The *i*th-ordered mean End of Maintenance time (EOM events are organized by order of occurrence within a single life history) for a <u>given part-card combination</u> is given by,

$$\overline{M}_i = \sum_{j=1}^{k} \frac{M_{ij}}{N_{ij}} + D_A \tag{3}$$

where,

$\overline{M}_i$ = *i*th-ordered mean EOM time

M_{ij} = *i*th-ordered EOM time in the *j*th life history

N_{ij} = number of occurrences as an *i*th-ordered EOM in the *j*th life history - either 1 (occurs) or 0 (does not occur)

k = number of life histories simulated.

The corresponding probability for the <u>given part-card combination</u> causing the *i*th-ordered EOM is given by,

$$P_i = \frac{\sum_{j=1}^{k} N_{ij}}{k} \tag{4}$$

where,

P_i = *i*th-ordered EOM probability.

The mean End of Repair times for given part-card-last repair action combinations and their associated probabilities are analyzed in the same manner.

The EOM event information can also be organized at the card-level (by card) rather than the system-level (order of occurrence). The associated means and probabilities are generated to provide probability distributions of end of maintenance dates on a card-basis rather than an ordering basis. The card-level EOM information tracked was organized for first-ordered events associated with each card. Therefore, the mean End of Maintenance time and corresponding probability for a given part-on-card combination concerning its first EOM event is given by eqns. (3) and (4) with i=1, respectively.

The EOR/EOM calculated information is the same for card-level and system-level analysis, except that the organizational structures of both analyses are different. The system-level analysis partitions events by order of their occurrences, while the card-level analysis partitions first ordered events by particular cards.

Inventory of Spare Cards, Throwaway, and Part Harvesting

The previously mentioned model draws from inventories as parts are needed, what happens when these inventories of spare parts are depleted? The model also includes inventories of spare cards that can be accessed once these part inventories are depleted, potentially further extending the legacy system support life. In the event that a part demand cannot be satisfied for a particular card that has available spare cards to draw from (see Fig. 2) the existing card is thrown away and replaced with one of the available spare cards. The action of throwaway and replacement of the existing card means the existing card must be discarded and replaced – accounted by the removal and re-sampling of its part demands from their corresponding reliability distributions.

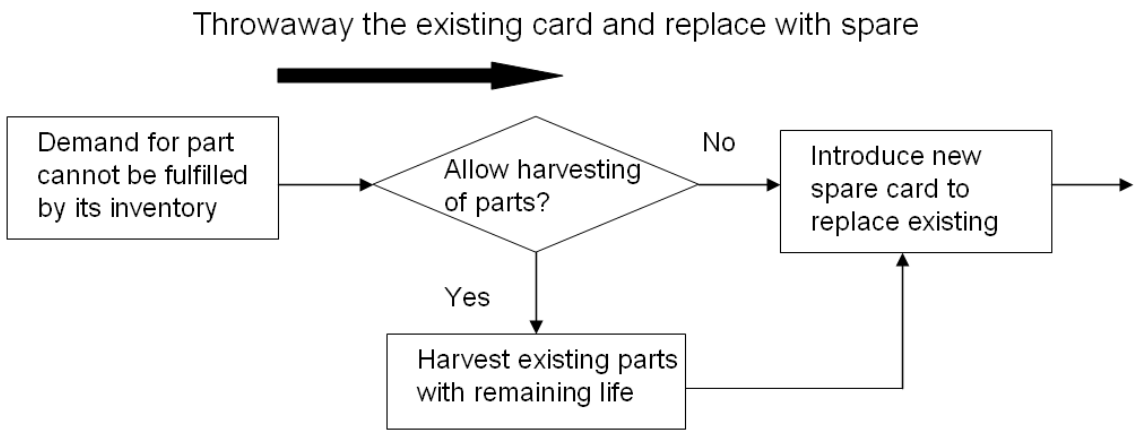

Fig. 2 Throwaway and part harvesting process

Another action that can be optionally taken is the harvesting or salvaging of parts off of discarded cards (the obsolescence mitigation strategy commonly known as reclamation). The action of part harvesting removes parts that have not failed and places them in a separate inventory of harvested parts. When inventories of spare parts and spare cards are depleted, this third inventory is then accessed and used until there are no more replacements available – a process that extends the end of maintenance date (i.e., system support life) of the system. The action of harvesting or reclamation will in general remove life from the part, a property that is also considered in the model and used in calculating the remaining fraction of useful life for the *i*th harvested part from the *j*th card, L_{ij}, given by,

$$L_{ij} = H_i \frac{FD_i - t_H}{FD_i - t_i} \tag{5}$$

where,

H_i = preserved life fraction of *i*th part incurred from the physical action of harvesting (0-1)
FD_i = *i*th part forecasted demand date
t_H = simulation time when harvesting action occurs
t_i = simulation time when *i*th part was introduced into system

The numerator in the fraction of eqn. (5) represents the remaining part life as the difference between the forecasted part's demand date and the simulation time at the time harvesting occurs. The denominator represents the part's time-to-failure when it is new. The remaining part life must be preserved as a fraction rather than a time-to-failure because it is likely the part will be used towards replacement on a different card where there may be discrepancies between the parts' reliabilities (represented by different probability distributions or distribution parameters. The remaining life fraction is then used to adjust future forecasted part demands used during part replacements when all other existing inventories are depleted.

The adjusted forecasted demand of the *i*th part from the *m*th card (*m* may equal *j*) , AFD_{im} , is then given by,

$$AFD_{im} = L_{ij} FD_{im} \tag{6}$$

where,

FD_{im} = *i*th part forecasted demand date from the *m*th card

Another possible issue associated with the storage of parts is degradation within inventories. The implementation of part degradation as an event within the model is straightforward. In discrete-event simulations, events can be described as anything that causes a change to the state of the system. The model interprets inventory degradation as an event that can occur at any instance in time. The model distinguishes between part failures and part degradation as two different types of events, but the model executes their processes in a similar manner.

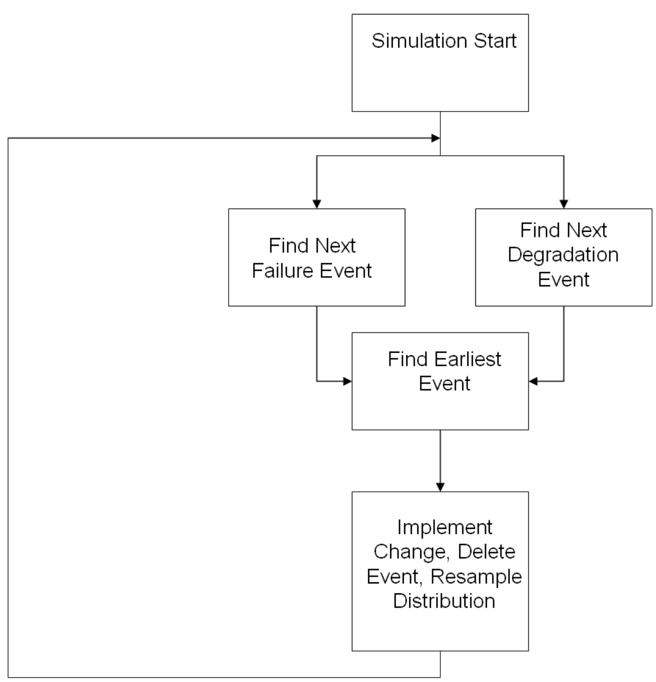

Fig. 3 Discrete-event simulation flow for multiple events

First, the model cycles through all possible types of events that can occur and finds the earliest date associated with each event type. The model then finds the earliest date among all event types and progresses to the earliest date, implements the appropriate changes to the system (depending on event type), removes the earliest date and resamples the distribution corresponding to the part that caused the event, Fig. 3. The process continues until specific simulation requirements can no longer be met or until part demands fail to be supported based upon existing inventories. Due to the nature of discrete-event simulation, the part inventory degradation event can be emulated through assignments of probability distributions representing the likelihood of a part degrading from inventory in a given time period. The forecasted degradation date for the *i*th part from the *j*th inventory, FDD_{ij} is given by,

$$FDD_{ij} = DD_{ij} + t \tag{7}$$

where,

$DD_{ij} =$ *i*th part forecasted degradation demand date from the *j*th inventory

t = current simulation time (starting at t =0).

The model currently treats inventory degradation as a recurring event that removes a part from inventory once the part's forecasted degradation demand date has been reached assuming there are remaining spares in inventory. The part's degradation distribution is then resampled and the next forecasted degradation demand date is calculated and its process continues until either the inventory of spares runs out or the EOM date is reached. This approach assumes that the degraded part is rightfully identifiable and discarded from inventory the moment it 'discretely' occurs; generally degraded parts remain in inventory until either inspection identifies the degraded part (which may require inspecting the entire lot) or the degraded part is identified after its failed use towards replacement. The degradation process flow can be seen in Fig. 4.

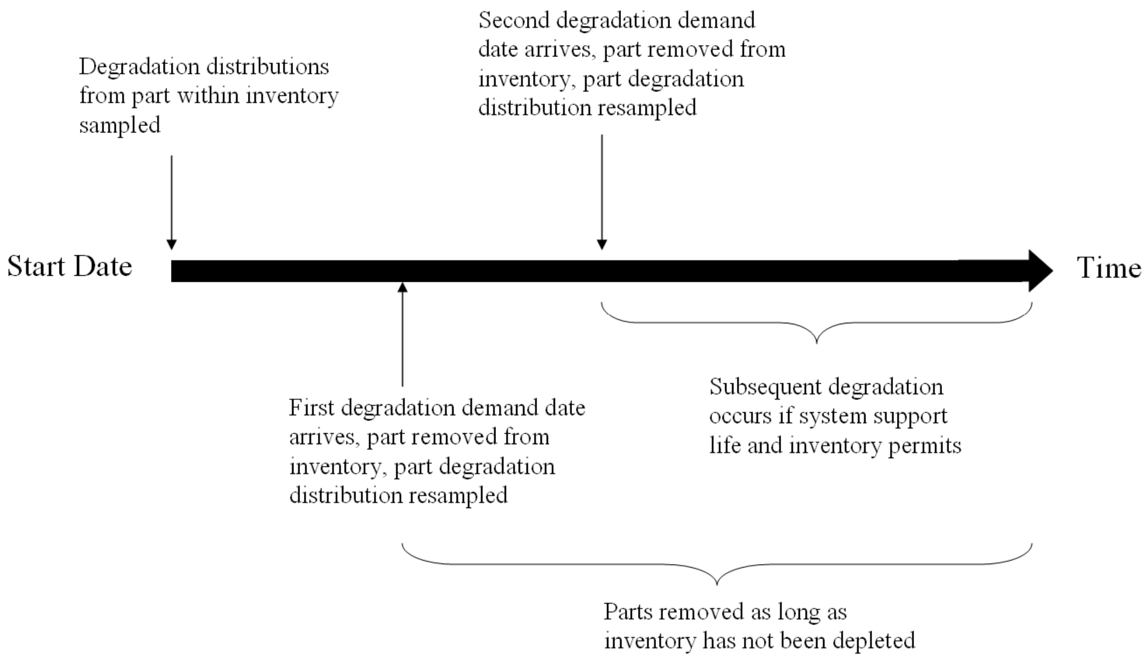

Fig. 4 Part degradation process flow

The process flow demonstrates the degradation for a single part within a single inventory. In the event that additional parts are assigned degradation distributions, additional process flows are added in parallel concerning each part involved (each process flow concerns a single part located in a specific inventory). The EOR/EOM model allows for part degradation probability distributions to be included for each part appearing in specific part inventories within the system.

IV. Test Case and Results

In order to exercise the developed model, a test case were developed for a real legacy system. The legacy system is comprised of unique cards, each card containing unique parts, and historical part failure histories. The objective of the test case is twofold: 1) to demonstrate the capability of the model, and 2) to observe the legacy system sustainment ramifications through different test scenarios (part harvesting, immediate first failures) while generating part failure distributions from observed failure histories.

The legacy system under investigation contains 117,000 instances of 70 different cards totaling 4.5 million unique obsolete parts. Each card has a unique number of fielded units and number of available spare cards to draw from. The provided legacy system was introduced in 1993 and the analysis begins on January 1, 2011. The legacy system is tracked for 1,000 system life histories regarding each test case scenario in order to construct probability distributions of the EOM dates.

The legacy system was examined using five different management assumptions representing 'worst-case' and 'best-case' scenarios for the legacy system and incorporating the use of part harvesting towards system sustainment. The 'best-case' scenario assumes that parts with no previous failure history within the system never fail and are not considered during EOR/EOM analysis. This assumption may be valid depending on the nature of the system and when the legacy system was introduced. The 'worst-case' scenario assumes that parts with no previous failure history experience their first failure at the beginning of the analysis and their failure distributions are synthesized based on this assumption. Each test case was tracked for 1,000 system life histories to construct probability distributions of EOM dates. The analysis ignored parts that were deemed non-obsolete and inventories of spare cards were included in all test cases and used before inventories of accumulated harvested parts were considered.

1. Best case- no harvesting
2. Worst case- no harvesting
3. Worst case- with harvesting

Run to the first EOM in the system

4. Worst case- no harvesting
5. Worst case- with harvesting

Run until every card has reached its first EOM (2050 max)

Fig. 5 Legacy system test cases

The first three test cases were analyzed to sustain the system until the first EOM date for the entire system (first instance that a part demand could not be fulfilled from available inventories) was reached. Test cases 4 and 5 sustain the system until one of two conditions was either met: 1) Run the simulation until every card type within the system has observed its first EOM date or 2) Run the simulation until the year 2050 has been reached. In both test cases 4 and 5, the first condition was never met so the simulation ran to 2050 and recorded the EOM events until that time. Test cases 4 and 5 were also ordered to organize EOM events and calculate associated means and probabilities on an card-level rather than system-level. This means that probability distributions of EOM dates were analyzed by individual cards rather than as a representation of the entire legacy system (by order of occurrence).

Parts Containing Significant Failure Histories with Right Censored Failure Data

A large number of failures have been observed to date for several specific parts in the example system. For these parts, the time to failure distributions can be determined using Maximum Likelihood Estimation (MLE) to find the best fit to 2-parameter Weibull distributions while accounting for the surviving parts using life data analysis software (Weibull++®).[3] The resulting failure distributions for these parts are shown in Fig. 6 and Fig. 7. The two lines on each graph represent the fitted failure distributions with and without the right-censored data.

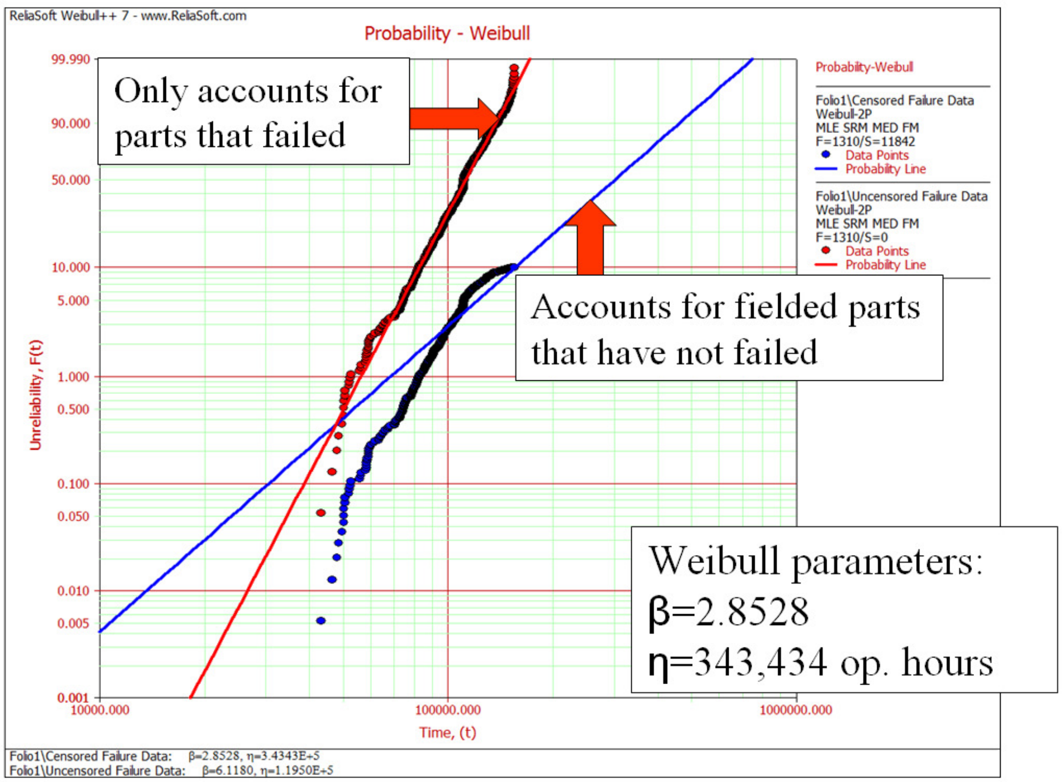

Fig. 6 Part number 3798-05 failure distribution. Both data sets are equal, one shows 10% unreliable, the other 100% unreliable (censored vs. uncensored).

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[3] The failure data is right censored because not all the fielded parts have failed to date. Right censoring occurs in reliability testing when some of the units in the population survive a test time period without failing.

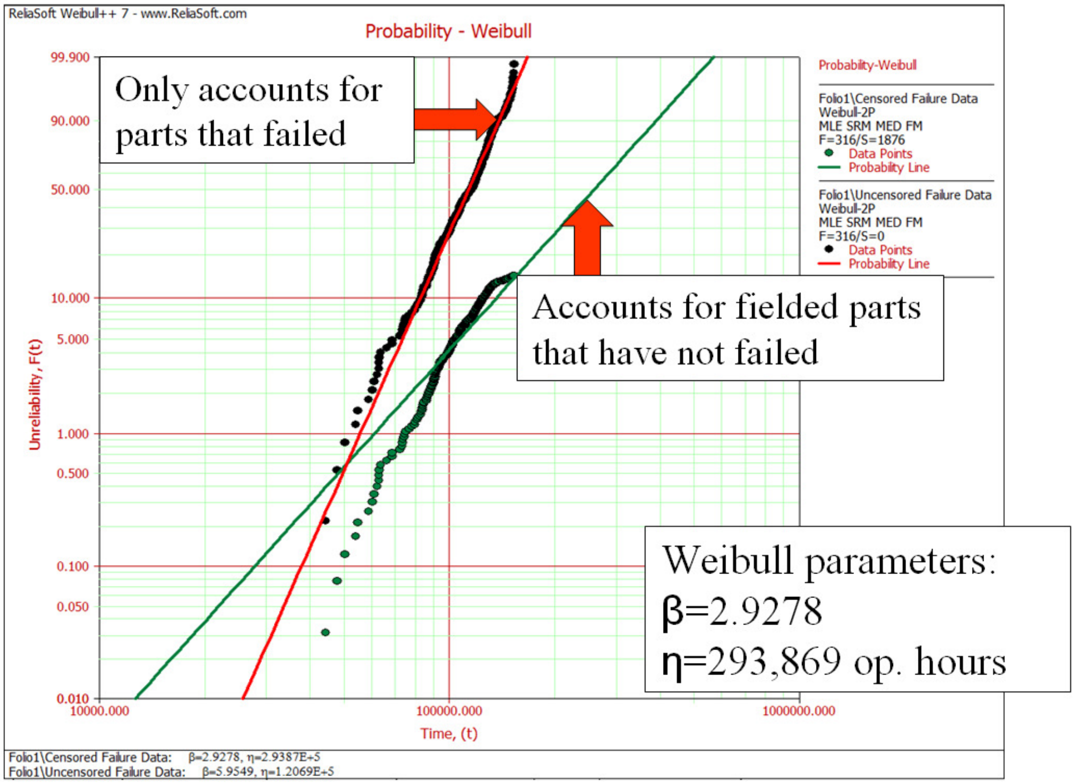


Fig. 7 Part number 5004-02 failure distribution. Both data sets are equal, one shows 10% unreliable, the other 100% unreliable (censored vs. uncensored).

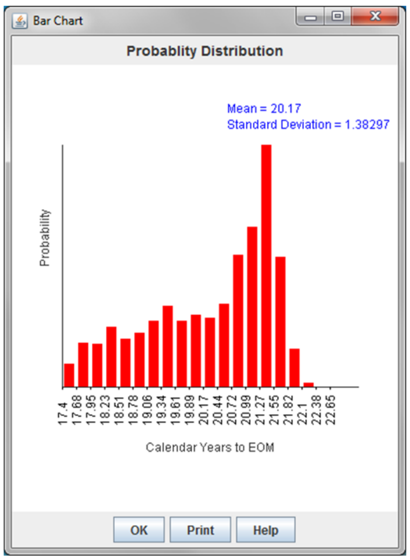
Other obsolete parts included in the legacy system had too few recorded failures to make MLE fitting practical and their failure distributions were therefore treated as uniform distributions created from historical failure data as described in eqns. (1) and (2).

No Failure of Non-Failed Parts and No Harvesting (Test Case 1) Results

The results for the first test case can be seen in Fig. 8. The mean time to the first EOM date for the system was approximately 20 years (2031). The left figure shows a distribution of the first EOM dates for the legacy system. On the basis of running 1,000 system life histories, that the following statement conclusions can be drawn:

- 50% probability that at least one instance of the system will be unsupportable by 2032
- ~100% (95.4%) probability of all instances of the system being supportable to 2028
- 100% probability that at least one instance of the system will be unsupportable by 2033

The right side of Fig. 8 shows the tabulated results of the six most probable causes of EOR/EOM events. The part that is most likely to result in the first-ordered EOM is part 5004-02 from Card 16 (35.7%) with a mean EOM time of 21.3 calendar years. This probability demonstrates that 357 out of 1000 life histories, the 5004-02 parts from Card 16 caused the first EOM in the system.



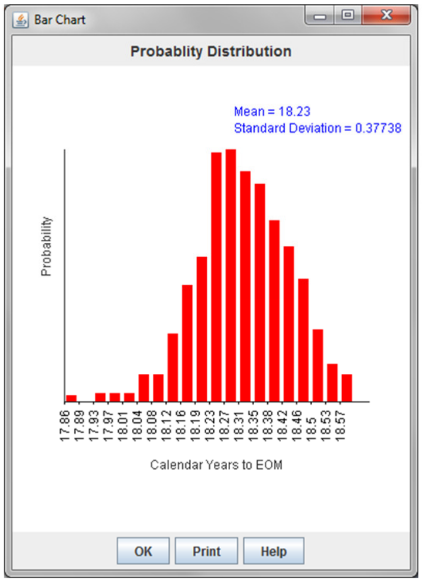
Part ID	Card ID	Mean EOM Time	Probability
5004-02	Card 16	2032.391	35.7%
6006-51	Card 4	2030.392	34.7%
4000-44	Card 24	2030.524	25.1%
4000-44	Card 18	2030.928	4.1%
4000-44	Card 23	2031.519	0.3%
4000-44	Card 25	2031.537	0.1%

Part ID	Repair Action	Mean EOR Time	Probability
6006-51	Card Stock	2030.331	28.5%
5004-02	Card Stock	2032.385	28.0%
4000-44	Card Stock	2030.648	23.1%
8008-11	RPB Inventory	2029.121	13.1%
7855-87	RPB Inventory	2031.556	2.7%
6488-04	RPB Inventory	2031.226	2.6%

Fig. 8 System-level EOM distribution (left), EOM (top right) and EOR (bottom right) results for Case 1

Immediate First Failure of Non-Failed Parts and No Harvesting (Test Case 2) Results

The results for the second test case can be seen in Fig. 9. The mean time to the first EOM date for the system was approximately 18 years (2029). The left figure shows a distribution of the first EOM dates for the legacy system. The right side of Fig. 9 shows the tabulated results of the six most probable causes of EOR/EOM events in the system.



Part ID	Card ID	Mean EOM Time	Probability
3834-35	Card 4	2029.303	34.2%
7003-88	Card 24	2029.309	25.7%
3834-35	Card 11	2029.401	11.7%
3834-35	Card 22	2029.374	10.4%
6006-51	Card 4	2028.509	6.0%
4000-44	Card 24	2028.441	5.6%

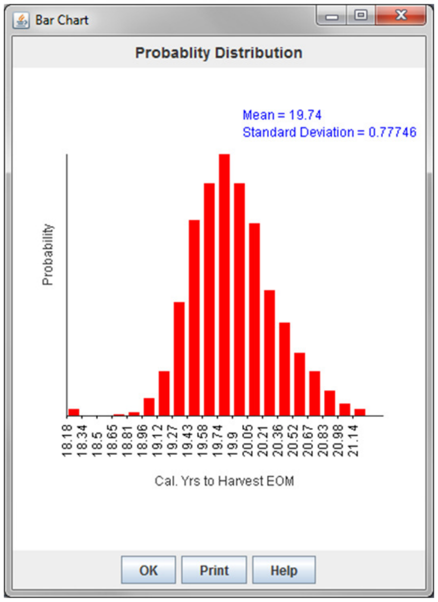
Part ID	Repair Action	Mean EOR Time	Probability
3834-35	Card Stock	2029.319	33.9%
7003-88	Card Stock	2029.301	15.2%
7855-87	RPB Inventory	2028.402	8.2%
6006-51	RPB Inventory	2027.763	6.6%
2000-04	RPB Inventory	2029.309	4.8%
6006-51	Card Stock	2028.48	4.8%

Fig. 9 System-level EOM distribution (left), EOM (top right) and EOR (bottom right) results for Case 2

The first End of Maintenance date decreases by two years due to the ‘worst-case’ assumption for obsolete parts with no failure histories. The differences between cases 1 and 2 show that there are different parts on different cards that cause the EOM date to be reached. The new parts identified in the case 2 results are due to including the first failure assumption as many legacy system supporters may not have a significant number of spare parts for parts that have never experienced failures before. Some of the same parts are identified in both sets of results—these parts also exhibit a decrease in their mean EOM arrival date due to additional card replacements that must be used to sustain the first failure parts.

No Failure of Non-Failed Parts and Harvesting (Test Case 3) Results

The results for the third test case can be seen in Fig. 10. The mean time to the first EOM date for the system was approximately 20 years (2031)—resulting in a two year gain in system sustainment due to the action of harvesting of parts.



Part ID	Card ID	Mean EOM Time	Probability
6262-95	Card 4	2030.909	52.3%
6262-95	Card 24	2030.964	25.8%
6262-95	Card 11	2030.826	13.8%
6006-51	Card 22	2028.52	7.3%
5004-02	Card 4	2032.207	0.3%
4000-44	Card 24	2027.861	0.1%

Part ID	Repair Action	Mean EOR Time	Probability
6262-95	Harvested	2030.951	32.2%
7855-87	RPB Inventory	2029.054	9.1%
1818-11	RPB Inventory	2029.805	9.0%
6006-51	RPB Inventory	2028.171	6.7%
6006-51	Card Stock	2028.354	5.9%
3985-00	RPB Inventory	2029.802	5.1%

Fig. 10 System-level EOM distribution (left), EOM (top right) and EOR (bottom right) results for Case 3

There are new introduced parts that cause the first EOM event. The part that causes the first EOM event occurs on three separate cards and accounts for causing the first EOM 92% of the time. This single part statistic demonstrates the action of part harvesting and how different cards are able to access the same harvested part for different cards (part's failure distribution is adjusted depending on the card that it is replaced) to further extend system support life. The first failure parts that had appeared in case 2 are no longer the root cause of the first EOM event due to the ability to harvest these first failure parts for later use.

Immediate First Failure of Non-Failed Parts and No Harvesting (Test Case 4) Results

The fourth test case initiates the change in analyses. The analysis ran until the year 2050, tracking all EOM events observed. The EOR/EOM model also can track specific cards through the system's support life showing how the fielded number of cards is removed over time due EOM events. Each of the tracked cards shown in Fig. 11 become unsupportable (all fielded cards are removed due to the failure of meeting part demands) by specific calendar dates. The card-level EOM results for the fourth test case can be seen in Fig. 12.

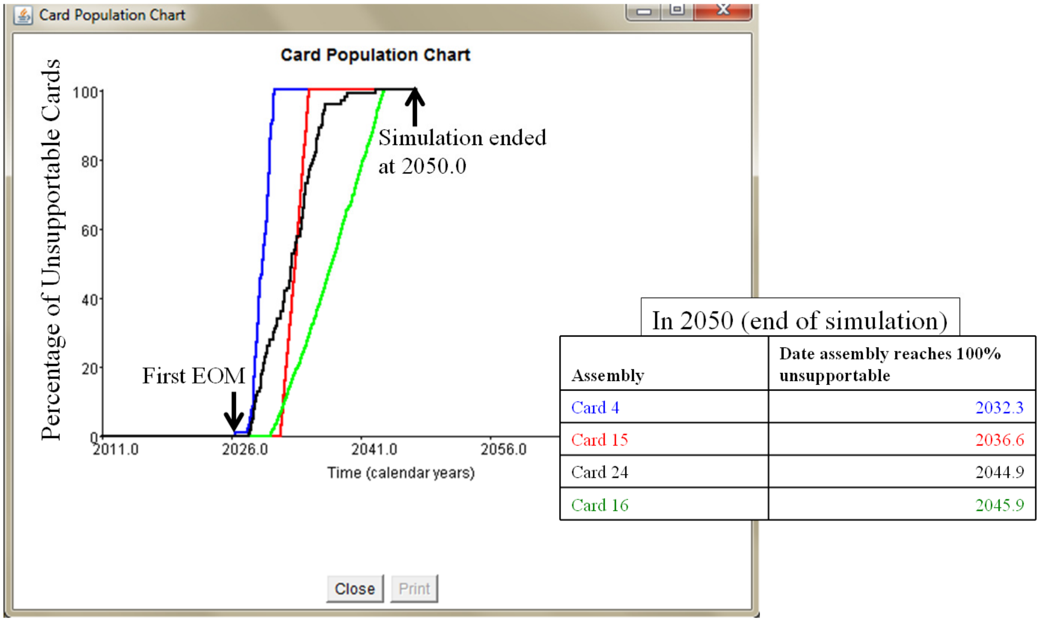
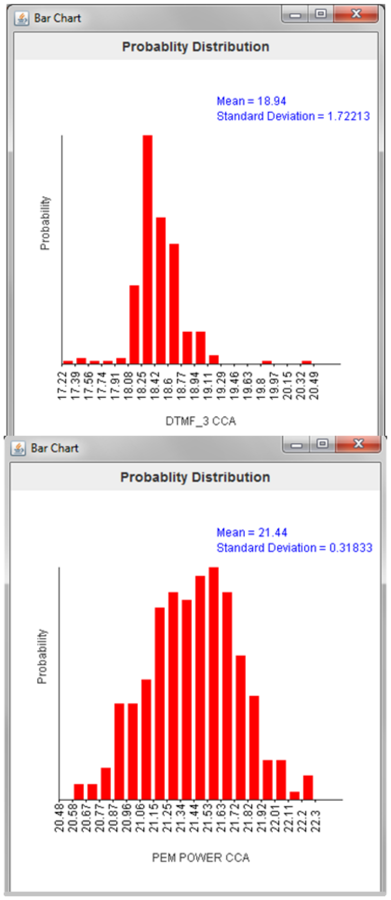


Fig. 11 Card-level support tracking and loss

The left figures in Fig. 12 show the card-level EOM probability distributions for specific cards in the legacy system. The table on the right side of Fig. 12 shows a list of the cards within the legacy system that observed at least one EOM event up until the calendar date (2050) when the simulation was terminated for a number of simulated life histories. 22 of the 70 cards in the legacy system exhibited first EOM dates prior to 2050 and probability distributions for each card that experienced EOM can be provided.



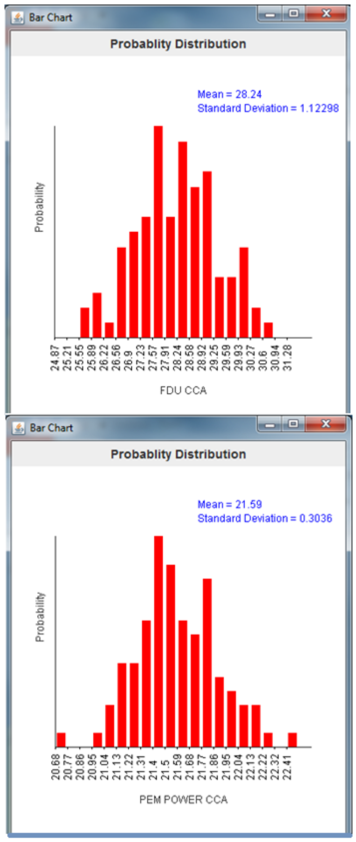
Part ID	Card ID	Mean EOM Time	Probability
3002-89	Card 1	2038.93	100.0%
2000-04	Card 2	2033.677	100.0%
8971-33	Card 3	2040.943	100.0%
3834-35	Card 4	2029.941	100.0%
1313-88	Card 5	2033.624	100.0%
0048-02	Card 6	2034.917	100.0%
5025-07	Card 7	2037.781	48.8%
7979-66	Card 8	2035.702	100.0%
3985-00	Card 9	2039.394	100.0%
8282-04	Card 10	2035.365	100.0%
5362-13	Card 11	2029.686	40.8%
9398-55	Card 12	2048.817	86.4%
1723-00	Card 13	2034.625	100.0%
6347-27	Card 14	2048.333	78.4%
6763-24	Card 15	2033.515	100.0%
5004-02	Card 16	2032.438	100.0%
5322-78	Card 17	2033.583	100.0%
5890-74	Card 18	2030.658	100.0%
6006-51	Card 22	2034.376	100.0%
3118-66	Card 23	2035.823	100.0%
4000-44	Card 24	2028.473	100.0%
4000-60	Card 25	2037.753	100.0%

Fig. 12 Card-level EOM distributions (left) and EOR/EOM results for Case 4 (right)

No Failure of Non-Failed Parts and Harvesting (Test Case 5) Results

The results for the last test case can be seen in Fig. 13, the only difference between cases 4 and 5 being the inclusion of part harvesting. The case 5 results were similar with case 4 where 22 of the 70 cards in the legacy system exhibited first EOM dates prior to 2050.

The common result is that part harvesting allows for card-level EOM dates to be delayed for significant periods of time. This result may not always be the case and depends on many different factors including parts' failure distributions and whether critical parts that cause card-level EOM events appear on multiple cards within the legacy system. In addition, the action of harvesting parts may not significantly delay card-level EOM dates when faced with high failure parts (due to excessive number of demands at a given time and lack of supply).



Part ID	Card ID	Mean EOM Time	Probability
3687-32	Card 1	2040.258	100.0%
2000-04	Card 2	2034.572	100.0%
5362-13	Card 3	2042.956	100.0%
6006-51	Card 4	2041.642	95.0%
1628-68	Card 5	2035.631	100.0%
1438-85	Card 6	2039.244	100.0%
4022-14	Card 7	2042.208	95.0%
5503-89	Card 8	2038.164	100.0%
3985-00	Card 9	2042.335	95.0%
9074-13	Card 10	2039.843	100.0%
6262-95	Card 11	2043.962	100.0%
9398-55	Card 12	2049.859	43.7%
1723-00	Card 13	2031.952	18.0%
6347-27	Card 14	2048.018	100.0%
3798-05	Card 15	2034.301	100.0%
5004-02	Card 16	2032.5587	100.0%
1818-11	Card 17	2034.437	100.0%
2008-84	Card 18	2038.71	83.0%
6006-51	Card 22	2036.528	100.0%
8897-53	Card 23	2034.627	40.3%
4000-44	Card 24	2028.78	98.7%
4000-60	Card 25	2047.68	52.6%

Fig. 13 Card-level EOM distributions (left) and EOR/EOM results for Case 5 (right)

IV. Discussion and Conclusions

The business of supporting legacy electronics systems is challenging due to mismatches between the system support life and the procurement lives of the systems' constitute components. In this paper we describe an End of Repair/End of Maintenance (EOR/EOM) model, which is a stochastic discrete-event simulation that follows the life history of a population of parts and cards and determines how long the system can be sustained based upon existing inventories of spare parts and cards, and optionally harvesting of parts off of existing cards to increase system support length.

The investigated legacy system under the 'best-case' scenario was able to remain supported on average until the calendar year of 2031. The introduced worst-case scenario assumption (immediate first failures) led to a decrease in system support life by two years. The implemented action of part harvesting (reclamation) extended the system support life by two years, allowing other cards to access commonly-used parts towards replacement actions. In test cases 4 and 5, some cards that became fully unsupportable by the year 2050 did so after approximately six years after the appearance of their first observed EOM event. The ability to track multiple EOM events provides the supporter with foreknowledge into what parts and/or cards will begin to 'drop-off-the-map' within the legacy system.

The EOR/EOM simulator model provides the legacy system supporter with insight about how long the system can be supported based on existing inventories of spare parts and cards including the critical identification of parts/cards (and their associated likelihoods) that cause system support loss. The model has the ability to generate part reliability distributions based on historical failure data (failures to date, first failure date, and number of fielded parts) for components having uncertain or unknown reliability information. The resulting forecasted system support life and its associated levels of uncertainty allow system supporters to make appropriate decisions (will further mitigation strategies need to be exercised or not) concerning system sustainment.

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