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Forecasting and Proactive Management of Obsolescence for Sustainment-Dominated Systems

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Abstract: Many technologies have life cycles that are shorter than the life cycle of the product they are in. Life cycle mismatches caused by the obsolescence of technology (and particularly the obsolescence of electronic parts) results in high sustainment costs for long field life systems, e.g., avionics and military systems. This paper describes a new methodology for forecasting electronic part obsolescence using a combination of life cycle curve forecasting and the determination of electronic part vendor-specific windows of obsolescence using data mining of historical last-order or last-ship dates. The new methodology not only enables more accurate obsolescence forecasts but can also generate forecasts for user-specified confidence levels. The methodology has been demonstrated on both individual parts and modules, and used to enable design refresh planning of systems and within the formation of material risk indices associated with the computation of sustainment dollars at risk.

1. Introduction: A significant problem facing many "high-tech" sustainment-dominated[1] systems is technology obsolescence, and no technology typifies the problem more than electronic part obsolescence, where electronic parts refers to integrated circuits and discrete passive components, [2,3]. The defense industry refers to electronic part obsolescence (and more generally technology obsolescence) as DMSMS – Diminishing Manufacturing Sources and Materials Shortages, [4]. In the past several decades, electronic technology has advanced rapidly causing electronic components to have a shortened procurement life span. Industry experts estimated that over 200,000 electronic components from over 100 manufacturers had become obsolete by the end 2003, [5]. Driven by the consumer electronics product sector, newer and better electronic components are being introduced frequently, rendering older components obsolete. Yet, sustainment-dominated systems such as aircraft avionics are often produced for many years and maintained for decades. Sustainment-dominated products particularly suffer the consequences of electronic part obsolescence because they have no control over their electronic part supply chain due to their low production volumes. This problem is especially prevalent in avionics and military systems, where systems often encounter obsolescence problems before they are fielded and always during their support life.

Part obsolescence dates (the date on which the part is no longer procurable from its original source) are important inputs during life cycle planning for long-field life, sustaintment-dominated products. Most electronic part obsolescence forecasting is based on the development of models for the part's life cycle. Traditional methods of life cycle forecasting utilized in commercially available tools and services are ordinal scale based approaches, in which the life cycle stage of the part is determined from an array of technological attributes, e.g., [6,7] and available in commercial tools such as TACTRAC™, Total Parts Plus, and Q-Star™. More general models based on technology trends have also appeared including a methodology based on forecasting part sales curves [8], and leading-indicator approaches [9]. Note, obsolescence forecasting is an "outside looking in" form

[1]This usage of the term "sustainment" in this paper does not infer environmental impacts, but is consistent with the Brundtland Report definition [1]: "Development that meets the needs of present generations without compromising the ability of future generations to meet their own needs". In the context considered in this paper, "present and future generations" refers to the users and maintainers of a system.

of product deletion modeling, e.g., [10], performed without access to internal knowledge of the manufacturer of the part.

Existing commercial forecasting tools are good at articulating the current state of a part's availability and identifying alternatives, but limited in their capability to forecast future obsolescence dates and do not generally provide quantitative confidence limits when predicting future obsolescence dates or risks. While a range of electronic part obsolescence mitigation approaches exist (see [3]), they are primarily reactive in nature (applied after obsolescence occurs). Strategic obsolescence management requires more accurate forecasts, or at least forecasts with a quantifiable accuracy. Better forecasts would open the door to the use of life cycle planning tools that could lead to more significant sustainment cost avoidance, [11].

This paper describes a new electronic part obsolescence forecasting methodology that is a combination of life cycle curve forecasting and the determination of electronic part vendor-specific windows of obsolescence using data mining of historical last-order or last-ship dates. The new methodology not only enables more accurate obsolescence forecasts but can also generate forecasts for user-specified confidence levels. The methodology has been demonstrated on both individual parts and modules. The paper also briefly describes the use of the obsolescence forecasts within a design refresh planning environment.

While successful electronic part obsolescence forecasting involves more than just predicting part-specific last order dates, being able to predict original vendor last order dates more accurately using a combination of market trending and data mining is an important component of an overall obsolescence risk forecasting strategy.

2. Obsolescence Forecasting Approach: The obsolescence forecasting approach discussed in this paper is an extension of a previously published life cycle curve forecasting methodology based on curve fitting sales data for an electronic part [8]. In the existing methodology, attributes of the curve fits (e.g., mean and standard deviation for sales data fitted with a Gaussian) are plotted and trend equations are created that can be used for predicting the life cycle curve of future versions of the part type (see Section 2.1 for an example). Similar procedures could be used to forecast the life cycle trends of secondary attributes such as bias level or package type. This obsolescence forecasting approach used a fixed "window of obsolescence" determined as a fixed number of standard deviations from the peak sales year of the part. This method was evaluated along with several other approaches by Northrop Grumman (in the Air Force CPOM program) and shown to be about the same accuracy as the commercial ordinal scale forecasting approaches.

2.1 Example Life Cycle Curve Forecasting Algorithm – Flash Memory: This subsection provides an example for life cycle curve forecasting for flash memory using the methodology in [8]. Figure 1 shows the historical and forecasted sales data for monolithic flash memory (from [12] and supplemented with more recent market numbers). The values of μ_p and σ_p that resulted from the best Gaussian fits to the data sets in Figure 1 were plotted; the trends for μ_p and σ_p are shown in Figures 2 and 3. For flash memory the trend in peak sales year and standard deviation in number of

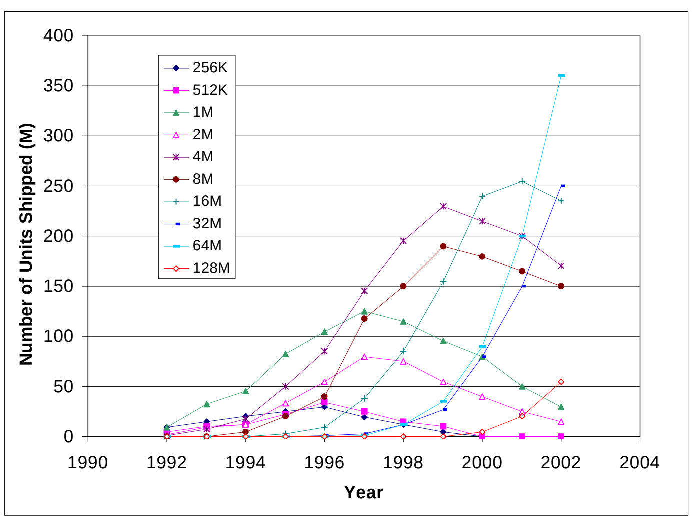

Figure 1: Historical and forecasted sales data for monolithic flash memory.

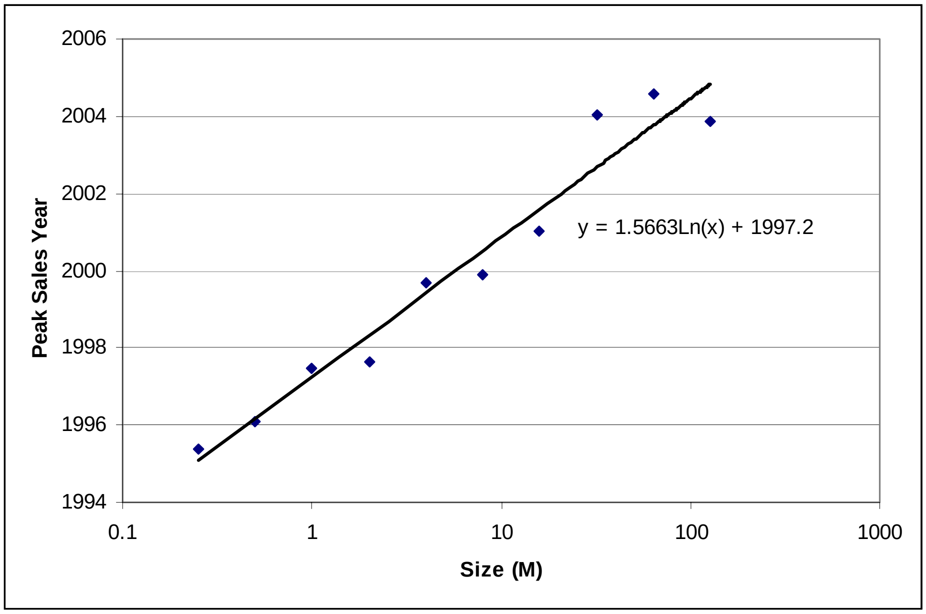

Figure 2: Trend equation for peak sales year (μ_p), for flash memory.

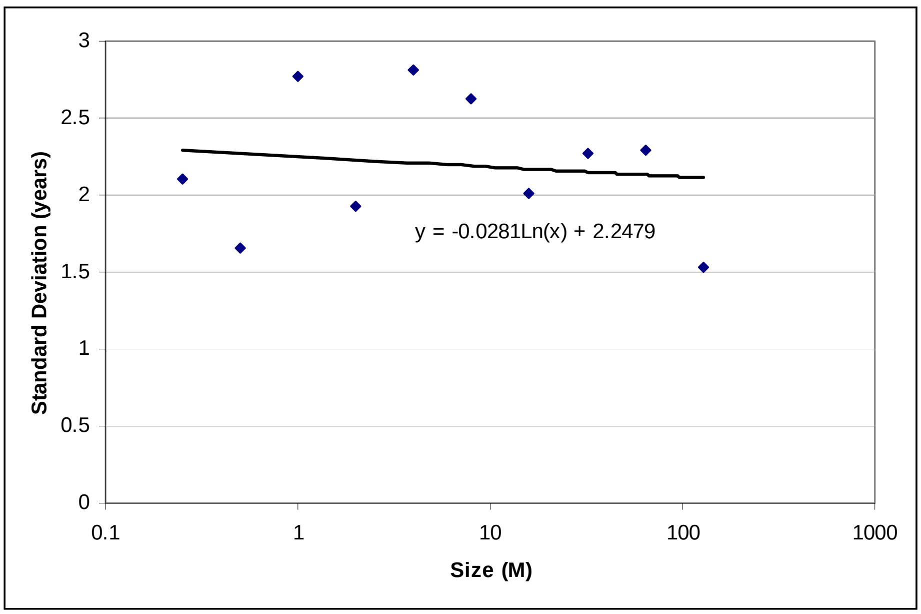

Figure 3: Trend equation for standard deviation (σ_p), for flash memory.

units shipped is given by,

$$\mu_p = 1.5663\ln(M) + 1997.2 \qquad (1)$$

$$\sigma_p = -0.0281\ln(M) + 2.2479 \qquad (2)$$

where M is the size of the flash memory chip in Megs.

The resulting trend equations can be used reproduce the life cycle curve for the parts that were used to create the relationships and for parts that are beyond the original dataset. For example, for M = 1 Meg, the trend equations gives μ_p = 1997.2 and σ_p = 2.25 (you can compare these to the actual data in Figure 1). Similarly, plugging in M = 512 Meg into (1) and (2) gives μ_p = 2007 and σ_p = 2.07 (this is a monolithic flash memory chip that was not included in the original dataset).

When generating the life cycle curve trend equations one should be careful not to mix mil-spec parts and commercial parts. For example, (1) and (2) were generated for commercial flash memory chips and should only be applied to commercial flash memory chips. Mil-spec flash memory chips (if they existed) would be considered a completely different part and unique trend equations would need to be developed for them.

2.2 Determining the Window of Obsolescence via Data Mining: The methodology described above provides a way to create or re-create the life cycle curve for a part type given its primary attribute. Where primary attributes are attributes that can be identified with the evolution of the part over time. In the original baseline methodology, [8], the "window of obsolescence" specification was defined to be at $2.5\sigma_p$ to $3.5\sigma_p$ after the peak sales date (μ_p). In reality, the window of obsolescence specification is not a constant but depends on numerous factors.

We suggest that the window of obsolescence specification is dependent on manufacturer-specific and part-specific business practices. For a particular part type (e.g., flash memory), historical last order date data is collected and sorted by manufacturer.[2] Each part instance (data entry) in the resulting sorted data has a specific value of primary attribute (e.g., 32M) for which the peak sales date (μ_p) and standard deviation (σ_p) can be computed using the previously created trend equations (for flash memory these are given in (1) and (2)). The last order date for the part instance is then normalized relative to the peak sales year. The normalization is performed for every part instance for the selected part type and manufacturer.

Next a histogram of the normalized vendor-specific last order dates is plotted; the histogram represents a probability distribution of when (relative to the peak sales year) the specific manufacturer obsoletes the part type. As an example, Figure 4 shows the histogram for

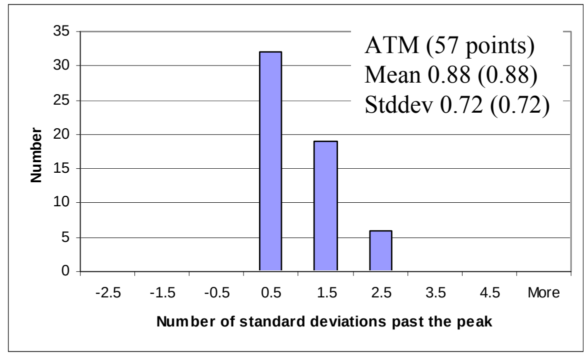

Figure 4: Atmel (ATM) flash memory last order dates.

Atmel (ATM) flash memory (based on 57 last order dates mined from PartMiner CAPS Expert). In order to quantify the manufacturer-specific obsolescence probability, the histogram is fit with a Gaussian form and the parameters of the fit are extracted, i.e., μ_{lo} and σ_{lo}. The window of obsolescence specification is then given by,

$$\text{Obsolescence window} = \mu_p + (\mu_{lo} \pm x\sigma_{lo})\sigma_p \quad (3)$$

where x depends on the confidence level desired (x = 1 you have a 68% confidence that you have the range that accurately predicts the obsolescence event, similarly, x = 2 represents 95% confidence).

By combining the life cycle curve trends and the ATM-specific obsolescence window, the resulting obsolescence dates for ATM flash memory are given by (4), which is a function of the size in Megs (M) and confidence level desired. Equation (4) assumes that the uncertainty in the window of obsolescence dominates the model uncertainty associated with the trend equations.

$$\text{Obsolescence date} = \underbrace{1.5663\ln(M)+1997.2}_{\text{Peak sales date}} + \overbrace{[0.88 \pm 0.72x]}^{\substack{\text{Number of standard deviations past}\\ \text{the peak for ATM Flash}}}\underbrace{(-0.0281\ln(M)+2.2479)}_{\substack{\text{Standard deviation}\\ \text{in sales data}}} \quad (4)$$

Using the methodology for the entire set of flash memory provided by PartMiner (262 data points), yields the results shown in Figure 5. The diagonal line in the plot shows exact agreement between prediction and actual. The error bars represent a 68% confidence level. The accuracy with which the improved algorithm

[2] The last order date is the last date that a manufacturer will accept an order for the part. After the last order date has passed, the part is considered to be obsolete. Obsolescence of a part does not necessarily correlate to the part's availability, i.e., some parts remain available through aftermarket sources and brokers for considerable periods of time after the original manufacturer has obsoleted them.

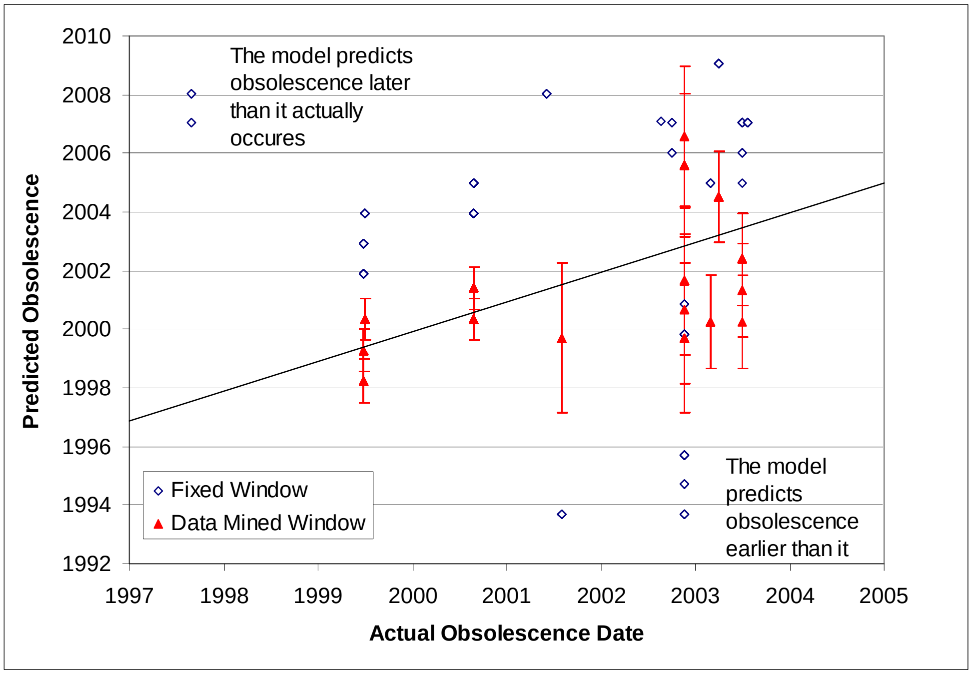

Figure 5: Forecasting results for monolithic flash memory chips. 262 flash memory chips plotted. Fixed Window model = assumes a fixed window of obsolescence specification of $2.5\sigma_p$ to $3.5\sigma_p$, Data Mined Window model = assumes the manufacturer-specific window of obsolescence.

forecasts the obsolescence of parts is a substantial improvement over the original algorithm.

2.3 Application of Data Mining Determined Windows of Obsolescence to Memory Modules: As a further demonstration of the methodology described in this paper, consider its application to memory modules that are made up of multiple chips. The obsolescence of memory modules is not generally dictated by the obsolescence of the memory chips that are embedded within them. Rather, the obsolescence of memory modules is related to the beginning of availability of monolithic replacements for identical amounts of memory. As an example, in Figure 6, the 16M DRAM module became obsolete when monolithic 16M DRAM chips became available.

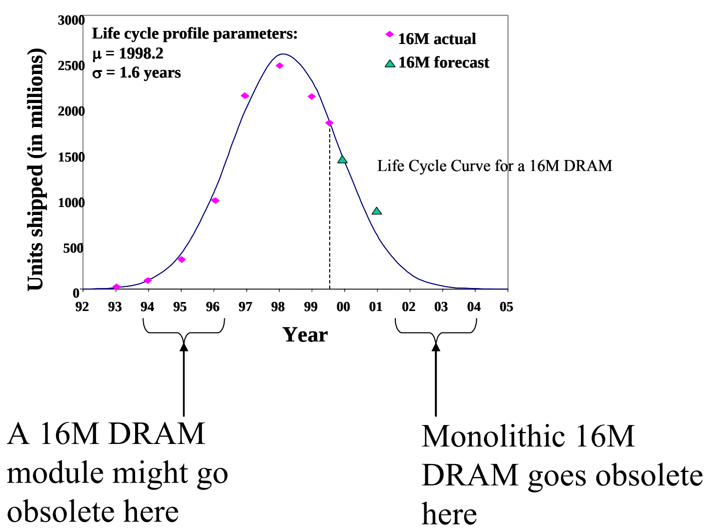

Figure 6: Obsolescence characteristics of DRAM memory modules vs. monolithic DRAM.

$$\text{Obsolescence date} = \underbrace{1991.8M^{0.0011}}_{\text{Peak sales date of } \textit{monolithic} \text{ DRAM}} - \overbrace{[0.9023x^3 - 4.7047x^2 + 13.167x - 11.935]}^{\text{Number of standard deviations before the peak of an equivalent } \textit{monolithic} \text{ DRAM}} \underbrace{(3.1M^{-0.23})}_{\text{Standard deviation in sales data for the}} \quad (5)$$

In the case of DRAM memory modules, the last order date data is collected. Each module instance (data entry) has a specific value of primary attribute (e.g., 16M). For each module instance, the peak sales date (μ_p) and standard deviation (σ_p) are computed for the monolithic equivalent. The last order date for the module instance is then mapped (normalized) to the standard deviations before the peak sales date for the monolithic equivalent. In the case of memory modules, there was no need to sort the data by vendor – all the vendors considered appear to be obsoleting memory modules based on the same driver. Figure 7 shows a curve fit of the resulting data mined last order dates mapped to the life cycle curve of the monolithic equivalents.

Armed with the relation shown in Figure 7 and the life cycle curve trends for DRAMs (e.g., see [8]), obsolescence dates for DRAM memory modules are given by (5).

In (5), $x = \log(M) \pm \alpha$, where the value of α depends on what confidence level you want (i.e., $\alpha = 0$ gives you the curve fit on the previous slide, $\alpha = 0.3$ gives ~90% confidence level).

3. The Use of Electronic Part Obsolescence Forecasts in Design Refresh Planning: Because of the long manufacturing and field lives associated with sustainment-dominated systems, they are usually refreshed or redesigned one or more times during their lives to update functionality and manage obsolescence. Unlike high-volume commercial products in which redesign is driven by improvements in manufacturing, equipment or technology; for sustainment-dominated systems, design refresh is often driven by technology obsolescence that would otherwise render the product un-producible and/or un-sustainable.

Ideally, a methodology that determines the best dates for design refreshes, and the optimum mixture of actions to take at those design refreshes is needed. The goal of refresh planning is to determine:

- When to design refresh
- What obsolete system components should be replaced at a specific design refresh (versus continuing with some other obsolescence mitigation strategy)
- What non-obsolete system components should be replaced at a specific design refresh.

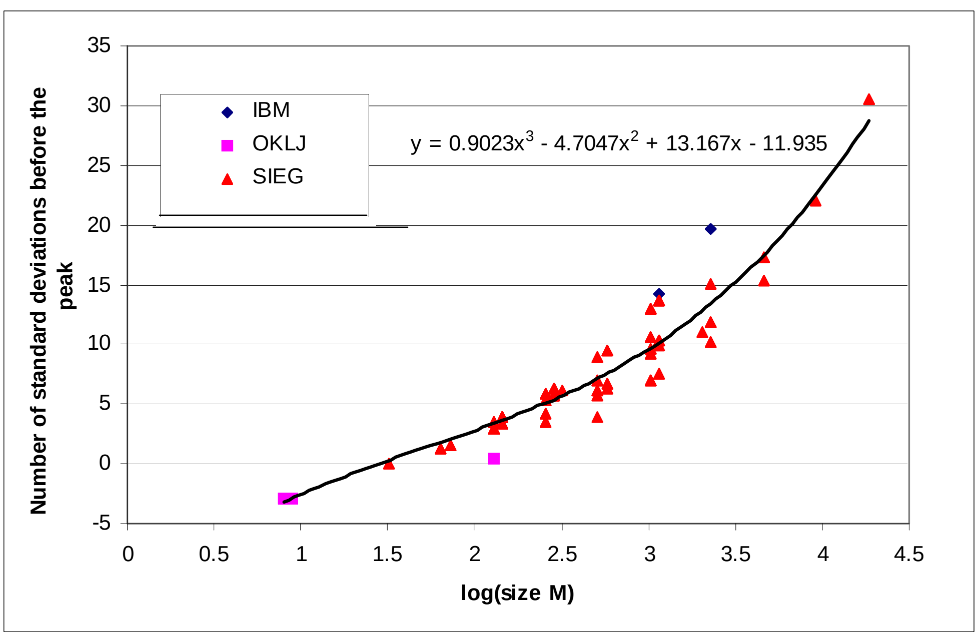

Figure 7: Data mined data mapping for DRAM memory modules.

Design refresh planning as it applies to obsolescence sensitive systems is discussed in more detail in [13].

For refresh planning, the obsolescence date forecasts for electronic parts are used as an input to a design refresh planning tool called MOCA (Mitigation of Obsolescence Cost Analysis). MOCA determines the part obsolescence impact on life cycle sustainment costs for long field life electronic systems based on future production projections, maintenance requirements and part obsolescence forecasts. Based on a detailed cost analysis model, the methodology determines the optimum design refresh plan during the life of the product (from design through operation and support). The design refresh plan consists of the number of design refresh activities, their respective calendar dates and content necessary to minimize the life cycle sustainment cost of the product. The methodology supports user determined short- and long-term obsolescence mitigation approaches on a per part basis, variable look-ahead times associated with design refreshes. MOCA is a stochastic tool in which all inputs can be probability distributions enabling MOCA to perform a robust optimization of refresh plan timing and content – this is an extremely important attribute given that the problem being addressed is fraught with uncertain and sparse data. For more detail on the MOCA tool, see [13].

An example refresh planning result generated by MOCA using a combination of obsolescence forecasts from commercial forecasting tools and from algorithms developed using the methodologies described in this paper is shown in Figure 8. MOCA generates results for all possible combinations of design refresh locations (dates) up to a user specified maximum number of design refreshes during the life of the product (3 refreshes, 20 year life in Figure 8 for example). The data points on the plot in Figure 8 each represent a different refresh plan (a refresh plan is a group of one or more design refreshed on specific dates during the lifetime of the unit). The "Mean Design Refresh Date" is the average date of the refresh in the plan (it is not important to the solution, i.e., it is just a way of spreading the results out along the horizontal axis for viewing). If the refresh plan only contains a single refresh, then the mean design refresh date is the actual date that the refresh takes place. The cost axis is a cost metric that is proportional to the life cycle cost of manufacturing and sustainment of all the units (design refresh and any associated re-qualification are included, but initial design and the original qualification cost is not included). This cost does not necessarily correspond to total life cycle costs for the system, but a smaller value of the metric does indicate lower life cycle cost. Note; 2005 was the date that the first

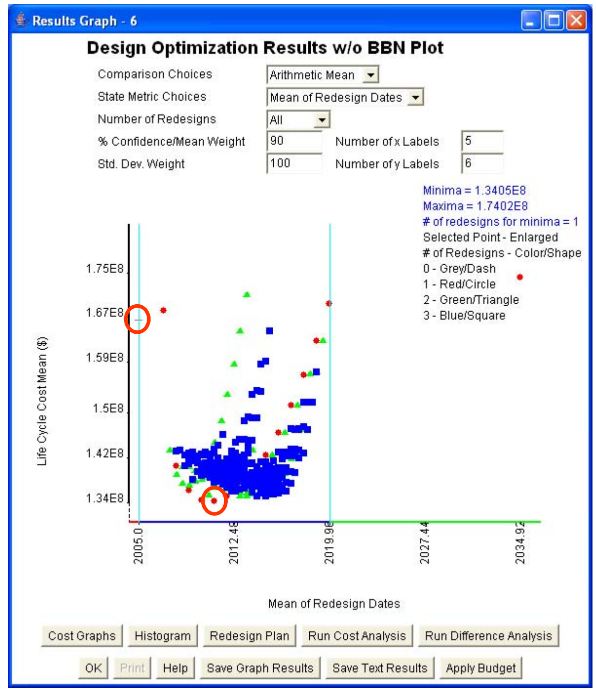

Figure 8: Example design refresh planning result from MOCA. The solution with no refreshes (upper left) and the optimum refresh plan (lower right) are circled.

production lot completed. However, this does not preclude in any way, parts used in the system becoming obsolete prior to 2005; in fact, some parts were forecasted to be obsolete prior to the completion of the first lot.

4. The Use of Electronic Part Obsolescence Forecasts to Enable Material Risk Index Formation: A Material Risk Index (MRI) approach analyzes a product's bill of materials and scores a supplier-specific part within the context of the enterprise using the part, e.g., [14]. MRIs are used to combine the risk prediction from obsolescence forecasting with organization-specific usage and supply chain knowledge in order to estimate the magnitude of sustainment dollars put at risk within a customer's organization by a part's obsolescence. MRIs work by cataloging replaceable subsystems by functionality (e.g., memory board, processor board, etc.), each cataloged subsystem is characterized by a profile that includes a set of time-dependent obsolescence risk impacts and an action level that defines the activities associated with design refreshment in the time period. The obsolescence risk in a particular period is translated into the fraction of subsystems of a certain type that require refreshment in the period. The cost of refreshment in the period is computed with an activity-based cost model. Summing all the refresh costs over all the subsystems provides an estimate of the sustainment cost in the period.

An activity-based cost ontology, which plays a key role in the formalization of cost information by capturing fundamental concepts in the product cost domain has been built that can be used in MRI calculation (see Figure 9), [15] and [16]. This cost ontology is used as a product cost knowledge base in a cost management system that is web-based for distributed access and collaboration and facilitates sharing of the common understanding of the role of costs among different types of engineers during design.

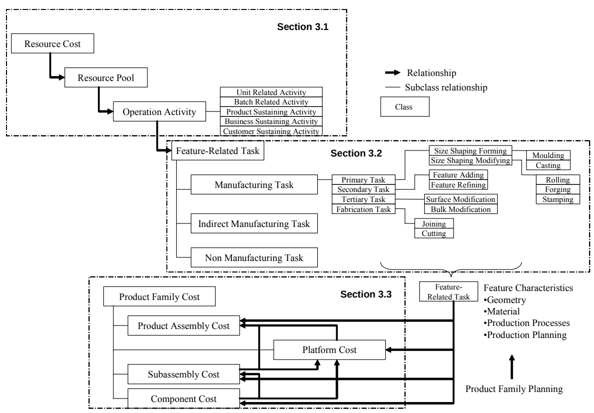

Figure 9: ABC ontology for product family planning, [15].

The forecasting algorithms discussed in this paper can be combined with the activity-based cost modeling to form an MRI calculation system for the assessment of application-specific obsolescence impact.

5. Discussion: Successful use of existing commercial electronic part obsolescence forecasting relies on the assumption that the forecasting is updated often and that the forecasts become better (more accurate) the closer you get to the actual obsolescence date. This implies that real forecasting value depends on an organization's ability to institute a continuous monitoring strategy and its ability to act quickly if a part accelerates toward obsolescence.[3] Unfortunately, the closer to the actual obsolescence event you get before the forecast converges, the less useful the forecast is, and thereby the value of pro-active refresh planning is limited. Being able to estimate the obsolescence date years in advance obviously provides many more options than knowing it 1 month in advance.

The methodology presented in this paper is a move in the direction of providing more accurate obsolescence forecasting with quantifiable confidence limits. However, the work presented in this paper does not represent a standalone solution. This approach needs to be combined with subjective information included in traditional obsolescence forecasting tools, e.g., number of sources, market share, technology factors, etc.

It is also worth pointing out that the two forecasting examples presented in this paper are straightforward applications of the methodology (they are "easy" cases). Not all part types have easily identifiable primary attributes (attributes that can be identified with the evolution of the part over time), therefore, we do not claim that the methodology will be useful on every part type.

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